AU/ACSC/BROWN/2009

AIR COMMAND AND STAFF COLLEGE

AIR UNIVERSITY

FORECASTING FUEL CONSUMPTION REQUIREMENTS FOR THE AIR FORCE FLYING HOUR PROGRAM USING POOLED TIME SERIES ANALYSIS

by

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A Research Report Submitted to the Faculty

In Partial Fulfillment of the Graduation Requirements

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Maxwell Air Force Base, Alabama

April 2009

Report Documentation Page

Form Approved
OMB No. 0704-0188

1. REPORT DATE	2. REPORT TYPE	3. DATES COVERED
APR 2009	**N/A**	**-**

4. TITLE AND SUBTITLE	
Forecasting Fuel Consumption Requirements For The Air Force Flying Hour Program Using Pooled Time Series Analysis	5a. CONTRACT NUMBER
	5b. GRANT NUMBER
	5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S)	5d. PROJECT NUMBER
	5e. TASK NUMBER
	5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) **Air Command And Staff College Air University Maxwell Air Force Base, Alabama**	8. PERFORMING ORGANIZATION REPORT NUMBER
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)	10. SPONSOR/MONITOR’S ACRONYM(S)
	11. SPONSOR/MONITOR’S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release, distribution unlimited

13. SUPPLEMENTARY NOTES
The original document contains color images.

14. ABSTRACT
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15. SUBJECT TERMS

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			
unclassified	**unclassified**	**unclassified**	**SAR**	**60**	

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Acknowledgements

First, I would like to thank Thomas Lies, Larry Clapper, and John Wallace from the Air Force Cost Analysis Agency (AFCAA) for providing the research topic, the data, and their time to support this effort. Second, this research is possible because of Richard K Hartley, the Deputy Assistant Secretary for Cost and Economics, Office of the Assistant Secretary of the Air Force for Financial Management and Comptroller, and his deputy, Ranae Woods. Finally, I would like to recognize Dr Edward D. White, professor of Statistics at the Air Force Institute of Technology (AFIT) for providing expert statistical consultation.

Abstract

The United States Coast Guard uses pooled time series analysis to develop a ship and aviation fuel requirement forecasting model. Given the volatility of aviation fuel prices and the USAF dependency on foreign oil, alternative fuel sources are a serious consideration and require forecasting models when conducting comparison studies. This research uses the Coast Guard's methodology to develop an Air Force aviation fuel requirements model for the Air Force Cost Analysis Agency (AFCAA). By pooling 1,442 historical consumption time series data points, two regression models are developed that predict aviation fuel requirements in gallons. The remaining 356 randomly excluded data points are then used to validate the two regression models. The research shows that 100 percent of the least squares estimated gallons consumed fell within a 95 percent confidence interval for the single and the sub macro-level models. However, the single and sub macro-level models are fundamentally flawed as both fail the underlying linear regression assumptions of normality, constant variance, and independence. Although the research produces two models that predict aviation fuel requirements well, the application of either the single or sub macro-level models are discourage without proper understanding of the underlying statistics provided.

I. Introduction

Problem Statement

The Air Force Cost Analysis Agency (AFCAA) is searching for a macro-level model that will forecast the United States Air Force (USAF) aviation fuel requirement. The forecasting model will serve two purposes. First, the model provides a cross-check or potential replacement to the current technique employed. Second, given the volatility of aviation fuel prices and the USAF dependency on foreign oil, alternative fuel sources are a serious consideration and require forecasting models when conducting comparison studies. This research seeks to determine if pooled time series analysis can develop a macro-level model to forecast the baseline Air Force aviation fuel requirement for alternative fuel source comparison studies.

General Issue

Annually, the AFCAA forecasts the aviation fuel requirement in gallons. Price factors are developed and published by The Office of the Secretary of Defense (OSD) to convert gallons to dollars for budgeting purposes. Currently, the AFCAA uses a five year historical average of aviation fuel consumption data to determine the Air Force requirement by mission design series (MDS) and major command (MAJCOM).

In the past, AFCAA has investigated potential predictive relationships using regression analysis. However, data sets at the MDS by MAJCOM levels are small and rarely produced any consistent results that are statistically significant. The lack of data is sometimes a deterrent to regression analysis. The Coast Guard uses a technique that pools detailed data to a macro-level increasing the size of the data set under analysis. By using the pooling technique, the effective data set swells to over 1,700 data points. The data increase will provide a more robust analysis to determine if a predictive relationship exists with statistically significant results.

Research Approach and Scope

This research paper uses a quantitative methodology using data pooling and multiple regression techniques. Historical aviation fuel consumption data and a multitude of potential explanatory variables, such as flying hours, sorties, mission type, weapon system type, and major command are provided by the AFCAA. However, the AFCAA database only captures nine data points for each weapon system within a major command. Although nine data points is sufficient to conduct regression analysis, this research seeks to determine relationships across multiple weapon systems and major commands. By pooling or combining all major commands and weapon system data, the potential exists to develop one macro aviation fuel requirement model based on known explanatory requirements using multiple regression analysis.

Several techniques to develop a macro-level forecasting model for aviation fuel requirements are available. In Chapter Two, some of these techniques are discussed. However, this research narrows the scope to the technique of pooled time series analysis in an effort to determine the potential application to predicting aviation fuel requirements.

Research Benefits

The research seeks to develop a macro-level forecasting model for USAF aviation fuel requirements. The model will either replace or provide a cross-check to the existing method that the AFCAA uses to predict aviation fuel requirements. The model will also serve to conduct alternative fuel comparison studies as the need to reduce foreign oil dependency increases.

Chapter Summary

This chapter proposes pooled times series analysis as a technique to develop a macro-level model to forecast USAF aviation fuel requirements. Chapter Two explores the United States and USAF foreign oil dependency and vulnerability, alternative fuel sources, and the

Coast Guard's pooled time series analysis model for forecasting ship and aviation fuel requirements. Chapter Three explains the methodology used to develop and test a potential Air Force aviation fuel requirement model using pooled times series analysis. Chapter Four presents the results of the model development. Chapter Five concludes with model recommendations.

II. Literature Review

Chapter Overview

The dependency on foreign oil places the United States and USAF in a vulnerable position as world competition increases for a global finite resource. For this reason, the United States is searching for alternative sources to fuel the economy and its military machine. To better understand the requirements of aviation fuel and potential alternative fuel source comparison studies this research will investigate existing methods or techniques to forecast aviation fuel requirements. Finally, the Coast Guard's pooled time series analysis ship and aviation forecasting model is examined for applicability to forecasting Air Force aviation fuel requirements.

The United States and USAF Dependency and Vulnerability on Foreign Oil

The United States far outpaces the world in oil consumption, consuming over 25 percent (7.6 billion barrels per year) of the world's 30 billion barrels of oil annually.[1] Without oil, America's economy and military machine would come to a screeching halt. America imports roughly 63 percent of its oil.[2] Foreign dependency on a high-demand finite resource jeopardizes U.S. national security.

In his 1994 book, *The Road to 2015*, John Peterson predicted United States dependence on Middle East foreign oil.[3] Table 1 shows a summary of the top oil importers. Of particular concern are the Organization of the Petroleum Exporting Countries (OPEC) that account for almost 50% of the oil imports.[4] Since 1989 United States oil imports have steadily increased, a favorable trend for the OPEC nations.[5] The majority of "world oil is in the Middle East, controlled by OPEC, a cartel of unfriendly, unstable regimes that already exercise too much

control over the world oil prices."[6] The reliance on such a vital resource to ensure national security is at the mercy of OPEC, which provides a staggering 30% of the United States overall demand for oil.[7] However, the greater threat is dependence on a finite resource.

Table 1: 2008 Top Importers from January—August[8]

Top Importers	Import Percent	Cummulative % Imports	Barrels in Thousands
1 Canada	18.6%	18.6%	592,199
2 Suadi Arabia*	12.0%	30.6%	380,632
3 Mexico	10.1%	40.7%	320,789
4 Venezuela*	9.3%	50.0%	295,205
5 Nigeria*	8.2%	58.1%	260,287
6 Iraq*	5.2%	63.3%	164,767
7 Algeria*	4.0%	67.4%	127,981
8 Angola*	4.0%	71.4%	127,651
9 Russia	3.7%	75.1%	118,767
10 Virgin Islands	2.5%	77.6%	79,491
11 Brazil	1.9%	79.5%	59,620
12 United Kingdom	1.7%	81.2%	53,312
13 Ecuador*	1.7%	82.8%	52,675
14 Colombia	1.6%	84.4%	51,190
15 Kuwait*	1.6%	86.0%	50,546
All others**	14.0%	100.0%	444,843
Totals	**100.0%**		**3,179,955**

*OPEC Nations
***Non-OPEC importers excluding Libya, Indonesia, and Arab Emirates*

Source of Imports	Distribution Percent	Barrels in Thousands
OPEC	47%	1,494,364
Non-OPEC	53%	1,685,591
Total	**100%**	**3,179,955**

The amount of oil remaining in the world is still debated. Although there is no definitive answer to "proven" and "unproven" reserves or "peak" production timelines, most agree that oil is a finite resource with an increased global demand. The oil industry currently discovers less than 40 percent in new oil necessary to prevent the base reserves from shirking.[9] In his book, *The End of Oil,* Paul Roberts predicts that the world will experience a peak in oil production in the year 2016 based upon current trends in global consumption and an estimated trillion barrels of remaining oil.[10] The importance of a peak is that production drastically declines.[11] However,

the greater concern is that non-OPEC oil is likely peak before OPEC bringing the world supply under "the control of a cartel with a history of rash behavior and dubious sympathy for the West."[12] A monumental concern for U.S. national security given the world's ever increasing demand for oil.

China, a distant second to the United States, accounts for only 7.9 percent of the world's consumption or less than a third (2.4 billion barrels per year) of the amount consumed by the United States.[13] With a population roughly four and a half times larger than the United States and an accelerated rate of industrialization, China's demand for oil is projected to reach 5.8 billion barrels per year by 2030.[14] Other rapidly industrializing nations, like India, are experiencing similar growth demands for oil. As the global demand for oil increases, the rate of exhausting reserves accelerates.

The Department of Defense (DOD) and in particular the USAF is highly dependent on oil. Aviation fuel is a large portion of the Air Force Flying Hour Program funding requirement. In fiscal year 2007 the Air Force consumed over two and a half billion gallons while flying over two million hours.[15] Per capita, only the Virgin Islands and the Netherlands Antilles consume more oil than the USAF.[16] This scale of consumption requires statistically significant estimates for future aviation fuel requirement.

The USAF has investigated the development of renewable energy sources such as bio-fuels as an alternative to the non-renewable hydrocarbon sources.[17] Some of the bio-fuels considered as potential alternatives include ethanol, biodiesel, algae, and biobutanol.[18] However, an analysis of alternative fuel sources is not the purpose of this study. This research will investigate potential models to forecast the aviation fuel baseline requirement by using multiple regression techniques. In an effort to reduce foreign oil dependency, a predictive model will

help the Air Force better understand the baseline requirement necessary for effective alternative fuel source comparison studies.

United States Energy Independence through Alternative Fuel Sources

The capacity of the United States to become energy independent and still meet current increasing demands without alternative energy sources is highly unlikely. The United States ranks third in oil production with 21.4 billion barrels of proven reserves.[19] However, an exhaustion of reserves would occur in four to five years if the United States relied solely on indigenous resources.[20] In the wake of constrained budgets, volatile fuel prices, and increased oil dependency on adversarial regimes, the United States must look to alternative fuel sources.[21] Although bio-fuels such as ethanol, biodiesel, algae, and biobutanol are not new alternatives, the production capacity, transportability, stability, and engine fuel compatibility challenges have not created a cost benefit to hydrocarbons.[22] However, when alternative fuel technologies satisfy USAF criteria the necessity to better understand alternative fuel source comparisons to the hydrocarbon baseline will require aviation fuel forecasting models.

Issues when Forecasting the USAF Aviation Fuel Requirement

The AFCAA determines the aviation fuels annual requirement. The current method takes an average of the past five fiscal years at the major command weapon system code level. The process is time consuming and very data intensive. The purpose of this research is to develop a macro-level mathematic relationship that forecasts aviation fuel requirements at the total Air Force level. This research employs the Coast Guard's application of pooled time series analysis to determine if known explanatory variables will establish a macro-level relationship to predict aviation fuel.

The AFCAA conducted a similar research in February of 1998 by developing a fuel consumption cost estimating relationship based on explanatory variables such as weight, speed, engine type, mission, and others.[23] Due to the scope and purpose of this research a full literature review is not included. However, using similar explanatory variables and applying a pooled time series methodology is worthy of future research.

Coast Guard Model Using Pooled Time Series Analysis

In August of 1999, the United States Coast Guard (USCG) Headquarters contracted the Logistics Management Institute (LMI) to develop models that forecast aircraft and ship fuel requirements.[24] The models that LMI developed used a data pooling technique with linear regression known as pooled time series analysis.[25] The fundamental components of a linear regression model are the intercept, slope, and the independent explanatory variable that explains the dependent variable. This research, like the USCG, investigates independent variables like flying hours to explain the fuel consumption or dependent variable. When data observations of the independent and dependent variables occur over time or across different groups, like weapon system codes, pooling the time series data is a common model building technique.[26] The advantage of pooling time series data increases the number of observable data points producing more powerful estimates.[27] The power comes in the models ability to accurately estimate fuel consumption requirements across a number of different platforms.

The three models LMI developed produced significant explanatory capability. The aircraft model explains 99 percent of the variation of fuel consumption using flying hours as the sole predictor.[28] The medium- and high-endurance cutter model and below-medium-endurance cutter model explained 87 and 90 percent of the variation of fuel consumption respectively using vessel hour operations as the sole predictor.[29] Although the LMI study declares the three models

statistically significant stating the parameter estimate pass the *t*-tests, the research paper does not include the test results for the assumptions of linear regression. This research will apply the same pooled time series analysis employed by LMI to develop a forecasting model for aviation fuel requirements for the USAF.

Chapter Summary

This chapter outlines the necessity for a macro-level model to better predict fuel requirements and alternative fuel source comparisons. Based on past research, the Coast Guard provides a methodology to develop a model to forecast aviation fuel requirements using pooled time series analysis. The pooling of data technique increases the number of data points. The larger data set creates a more robust regression analysis to better understand the predictive power of potential models.

III. Methodology

Chapter Review

The Coast Guard uses pooled time series analysis to develop mathematical relationships to forecasts aviation and ship fuel requirements. This research seeks to develop and employ similar mathematical relationships by applying the pooled time series analysis to forecast Air Force aviation fuel requirements. The chapter explains the data preparation and pooling technique, introduces the potential explanatory variables used in the regression analysis, and describes the theoretical tests necessary to claim a statistically significant model. The chapter continues by explaining the methodology used to validate the predictive capability of a theoretically sound model. Finally, the method to assess the risk and uncertainty of model predictions is explained.

Preparing and Pooling the Data

The data used for the regression analysis is provided by the AFCAA. The composition of the historical data includes nine fiscal years of both numerical and categorical predictors that are delineated by pre and post 9/11. The aviation fuel consumption in gallons, flying hours, and sorties are the three numerical predictors and the categorical predictors includes MAJCOM, weapon system code, weapon system type, and mission type. The three numerical predictors are further delineated into combat or training fuel consumption, flying hours, and sorties. The complete data set provides 2,404 data points for analysis. However, some of the data points are justifiably removed due to recording error or incompleteness.

The final dataset contains 1,778 data points after removing records that did not have flying hours, gallons consumed, or the mission was unknown. Several hundred of the data points

had no recorded PAA and five did not have the number of sorties recorded. However, because the PAA and sorties were not significant predictors those data points remained in the final dataset. Upon completion of the dataset preparation the method of pooling time series analysis is employed.

The term "pooling time series analysis" refers to the data arrangement and the analysis technique. First, "pooling" is the process of combining similar data into one dataset to increase the number of observations when conducting the analysis. Currently, the AFCAA takes an historical average of the aviation fuel consumed by a particular weapon system code within a particular MAJCOM. However, nine data points is not ideal when using regression analysis to determine statistically significant mathematical relationships. Although many of the weapon systems at the MAJCOM level show strong relationship between gallon consumed and flying hours this research seeks to discover a macro-level model to avoid the time consuming process of developing a predictive model for each weapon system code with a MAJCOM.

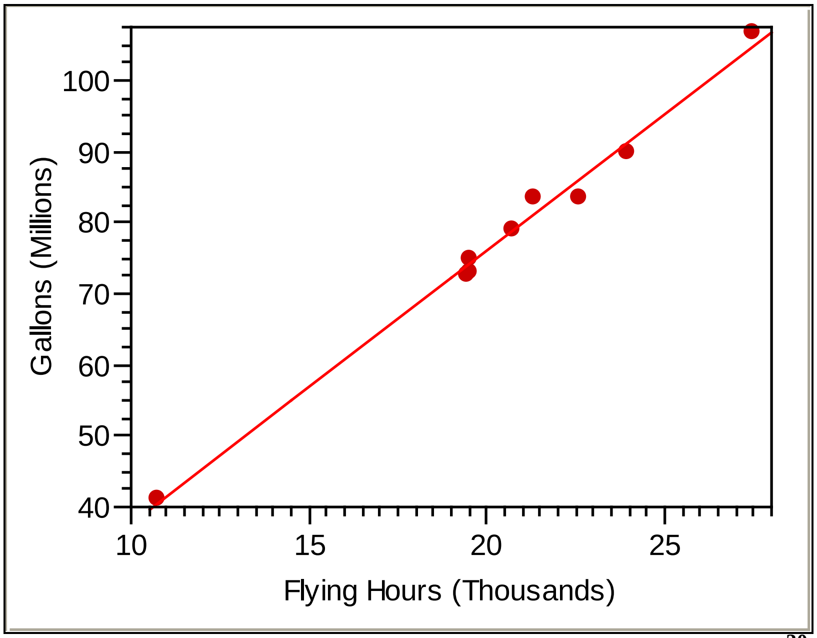

Figure 1: ACC B-1B Gallons Consumed by Flying Hours[30]

Figures 1 and 2 illustrate the pooling data technique using the bomber weapon systems. Figure 1 shows a strong relationship between gallons consumed and flying hours for the B-1B in Air Combat Command (ACC). Figure 2 shows the method of pooling by combining all of the bombing weapon systems across all of the MAJCOMs. The large data points are the B-1Bs in ACC and the remaining data points represent the B-2As, B-52s, and the remaining B-1Bs from other applicable MAJCOMs. The benefit of pooling the data is the creation of one macro-level model that forecasts the aviation fuel requirement for bombers given the programmed flying hours for any given fiscal year. The increase in data points enhances the fidelity of the statistical significance and the potential predictive power of the mathematical relationship. The purpose of this research is to pool the time series data to develop a macro-level model that is statistically significant to justify the use of the model to forecast aviation fuel requirements.

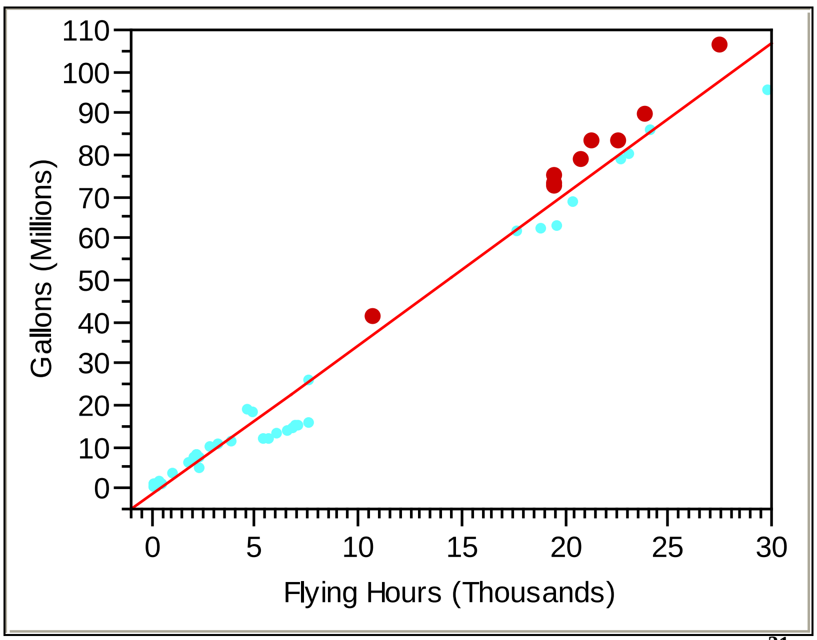

Figure 2: Bomber Gallons Consumed by Flying Hours[31]

Multiple Regression Analysis

Multiple regression is used to determine if there is a mathematical relationship between gallons of aviation fuel consumed and possible predictors that are known prior to forecasting a

new aviation fuel requirement. To build the fuel requirement regression model, five categorical (nominal) and three numerical (continuous) predictor variables are tested for significant relationships.[32] The five categorical predictors are MAJCOM, weapon system code, weapon system type, mission type, and pre or post 911 data (see appendix A, Table 7). The three numerical predictors are the flying hours by MAJCOM and weapon system code, the number of sorties flown by MAJCOM and weapon system code, and the primary assigned aircraft (PAA) or number of a particular weapon system code with a MAJCOM. Using JMP Statistical Analysis Software, mathematical relationships are investigated and tested for theoretical soundness to forecast aviation fuel requirements.

Statistical Significant Tests

To test for the statistical reliability of potential regression models an analysis is conducted to determine if any influential data points exist that bias selected explanatory variables and to test the model assumptions for normality, constant variance, and independence. The test for possible influential data points is achieved by plotting Cook's D influence statistic which indicates observations with large effects on parameter estimates.[33] The x-axis labeled "Rows" is the number of data points delineated by MAJCOM and weapon system code.

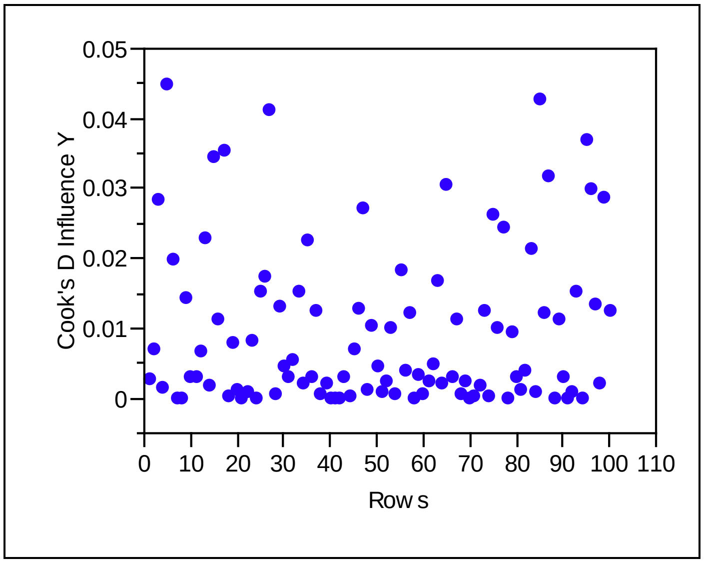

Figure 3: Cook's D Influential Data Points Test Example[34]

When values are greater than 0.5 the observation is considered influential.[35] Figure 3 displays an ideal example of Cook's D influential statistic plotted showing no outlying data points.

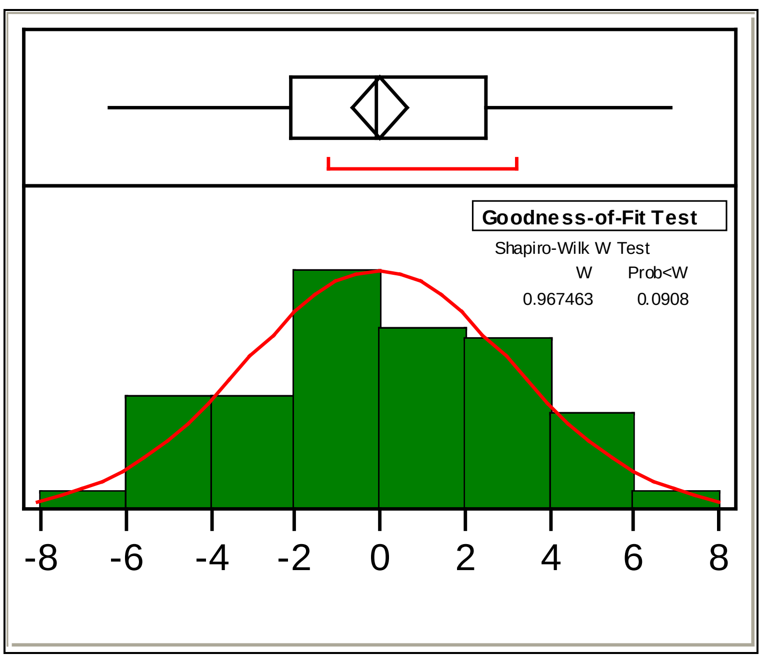

Figure 4: Residual Normality Test Example[36]

The purpose of testing for normally distributed residuals ensures the validity of the overall *F* and *t*-tests. The *F*-test indicates that the overall model is significant.[37] When there are

several explanatory variables, the *t*-test indicates the significance of multiple predictors. Additionally, inferences concerning the variability of model parameters hinge upon normally distributed residuals. To determine if the regression model residuals are normally distributed a goodness-of-fit (GOF) is conducted.[38] The residuals are normally distributed when the *p*-value is greater than 0.05.[39] Figure 4 graphically depicts an example of normally distributed residuals with a *p*-value greater than 0.05.

The test for constant variance and independence is determined graphically by using a scatter plot of the predicted values versus the residuals values. When constant variance and independence is present the residuals are evenly distributed around the line 0 depicted in Figure 5.[40] When constant variance is not present the fidelity of the predicted values is compromised. Transforming the dependent variable is a potential correction for constant variance.

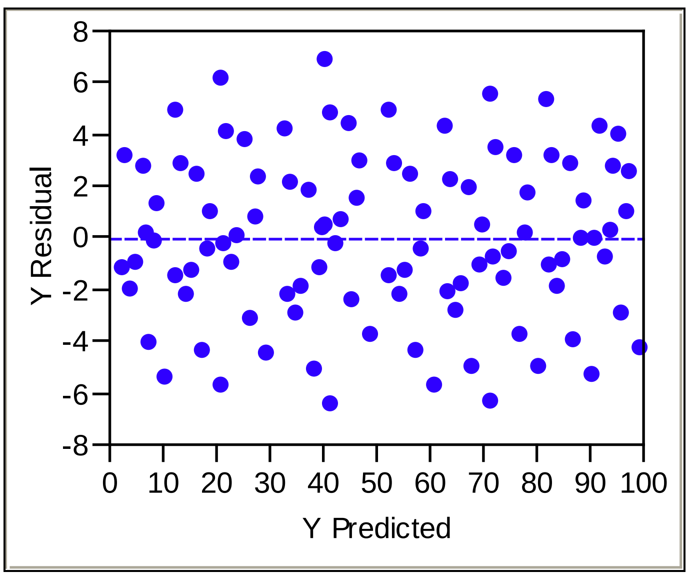

Figure 5: Example of Constant Variance in the Residual by Predicted Plot[41]

<u>Model Validation</u>

To validate the robustness of the regression models, a random sample of 20 percent of the data is excluded from the model development. Once the model is developed and determined statistically significant the remaining 20 percent of the randomly selected data is used to test the

predictive capability of the model. The regression model determines what explanatory variables are significant. The same explanatory variables from the excluded data are entered into the regression model to produce predictions. A successful validation is achieved if the model predictions fall within a 95 percent prediction interval. The validation will demonstrate that there is not an over-fit of the data to build the regression model.[42]

Developing Uncertainty and Risk Analysis

The purpose of this research is to develop a regression model that predicts the aviation fuel requirement. However, the usefulness of predictions often hinges on the understanding of the uncertainty and risk of a model's output. Assuming the regression model passes the test of normality and constant variance, the mean and standard deviation of the prediction is the basis for understanding the uncertainty and risk. In this case, uncertainty is the range of potential outcomes across a normal probability distribution for any one observation defined by the model's mean and standard deviation. The distribution of uncertainty helps a decision maker better understand the probability of potential risks or the probability of an unfavorable outcome. Any given prediction of a linear regression model is the mean and has an associated standard deviation. Using Monte Carlo simulation, the model mean prediction and standard deviation produce a theoretical normal distribution that will quantify the uncertainty and risk of forecasting aviation fuel requirements.

Chapter Summary

This chapter explains the proposed methodology to predict aviation fuel requirements. A discussion of preparing and pooling the data provides the background to understanding the nature of the dataset that is used for regression analysis. The tests for statistical significance are explained to ensure the fundamental assumptions of linear regression are met. The method of

validating the forecasting model is presented. Finally, an explanation of the process to assess the uncertainty and risk of the model predictions is provided.

IV. Results

Chapter Overview

Chapter Three outlined the methodology to predict aviation fuel requirements. This chapter presents the results of applying pooled times series analysis to develop a forecasting model for aviation fuel requirements. First, the aviation fuel regression models are displayed and explained. Second, the statistical significant tests are presented. Finally, the model validation results are discussed.

Single Macro-Level Aviation Fuel Regression Model

The regression analysis looked at several potential mathematical relationship broken into single and sub macro-level models. The single macro-level model used 80 percent of the data to develop a mathematical relationship and the remaining 20 percent is set aside for model validation. This research develops both single and sub macro-level models for comparison purposes. Figure 6 shows a scatter plot of the data used to develop a mathematical relationship for the single macro-level model in terms of gallons consumed and flying hours.

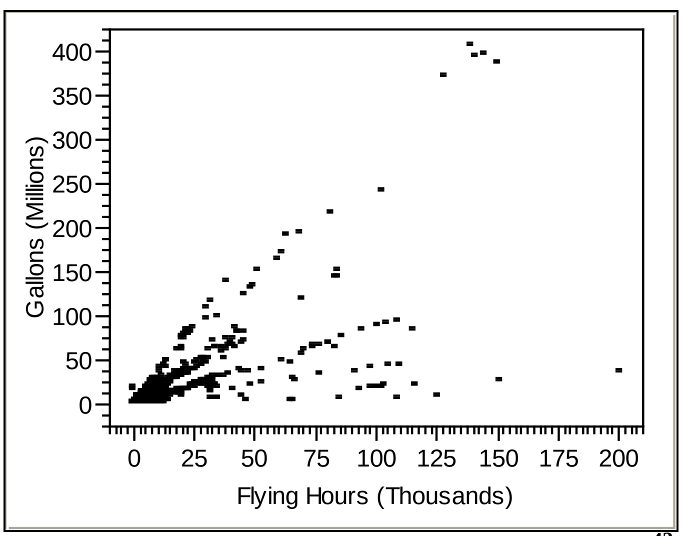

Figure 6: Single Macro-Level Data Scatter Plot[43]

The scatter plot shows that there is no linear relationship between gallons and flying hours alone. However, Figure 6 does clearly show that there are definite sub groups that graphically indicate linear relationships which are discussed later in the chapter. The purpose of this section of the study is to develop a single macro-level model by introducing additional predictor variables that will explain actual fuel consumption data. Figure 7 graphically illustrates the least squares estimated gallons in millions by the model's predicted gallons in millions. The least squares estimated gallons are arranged closely along the model's predicted gallons regression line, demonstrating that our regression model predicts gallons well. However, a closer look at the table of statistics reveals concerns about the soundness of the model.

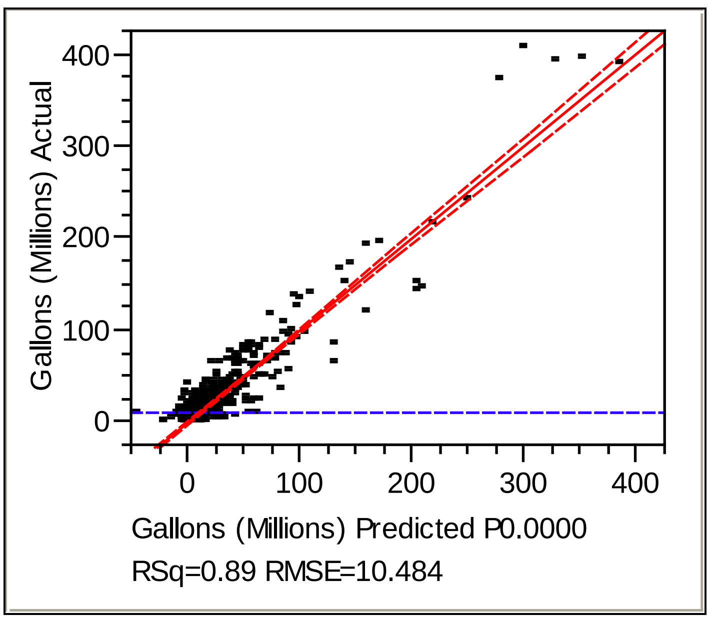

Figure 7: Initial Least Squares Estimated Gallons by Predicted Gallons Plot[44]

First, the focus of the table of statistics is the adjusted R^2, *F*-test, *t*-tests, and variance inflation factor (*VIF*). The adjusted R^2 measures the model's capability to predict the gallons. The adjusted R^2 is preferred over the R^2 because it compares across models with different numbers of parameters by using the degrees of freedom in its computation.[45] The *F*-test determines the overall model significance and the *t*-test determines the significance of each

explanatory variable. When the *p*-values are less than 0.05 the model or individual predictors are considered significant. The *VIF* is a statistical measurement that tests for multicollinearity, or correlation between predictor variables.[46] When the *VIF* is greater than or equal to 10, multicollinearity may exist and could decrease the fidelity of any given point prediction.[47]

Table 2: Initial Single Macro-Level Table of Statistics[48]

Single Macro-Level Summary of Fit					
RSquare					0.89304
RSquare Adj					**0.89251**
Root Mean Square Error					10.48406
Mean of Response					12.01761
Observations (or Sum Wgts)					1422
Analysis of Variance (ANOVA)					
Source		**DF**	**Σ Squares**	**μ Square**	**F Ratio**
Model		7	1297698.2	185385	1686.618
Error		1414	155420.5	110	**Prob > F**
C. Total		1421	1453118.6		**0.0000**
Parameter Estimates					
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**	**VIF**
Intercept	-1.82307	0.33588	-5.43	**<.0001**	--
Combat FH(K)	3.25529	0.03900	83.47	**0.0000**	1.21605
Training FH (K)	**2.23308**	**0.07924**	**28.18**	**<.0001**	**22.60263**
Total Sorties	**-0.00238**	**0.00010**	**-22.96**	**<.0001**	**20.24559**
C-130H	-18.39458	1.83450	-10.03	**<.0001**	1.04525
F-15C	14.56145	1.58155	9.21	**<.0001**	1.01293
T-1A	-91.29420	4.75890	-19.18	**<.0001**	1.84264
Bombers/Tankers	13.58475	0.96535	14.07	**<.0001**	1.13089

Table 2 presents the results of a potential model. Combat and training flying hours, C-130H, F-15C, T-1A, and the group Bombers/Tankers are the significant predictors. The Bomber/Tanker group combines the B-1A, B-2B, B-52H, C-141B, C-17A, C-5A/B/C, and the KC-10A. The adjusted R^2 of 0.89 indicates that the model predicts gallons well and is not overly affected by the seven predictor variables selected. The *F* and *t*-tests all show *p*-values that are

significant indicating that the overall model and individual predictor variables are statistically significant. However, the training flying hours and total sorties predictors both report *VIF* values well above five suggesting multicollinearity (see Appendix C for predictor variables correlation matrix). Because the training flying hours explain more of the variation, the total sorties predictor variable is eliminated from the model. Figure 8 shows the new least squares estimated gallons in millions by the predicted gallons in millions without including total sorties.

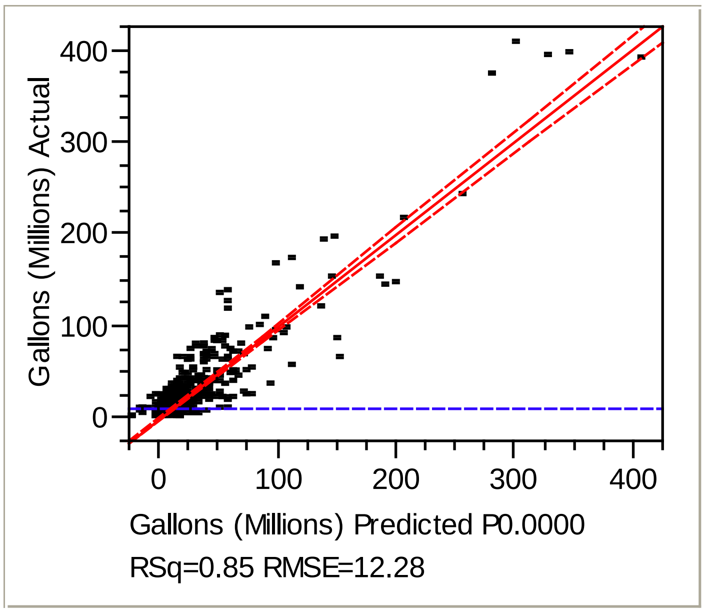

Figure 8: Final Least Squares Estimated Gallons by Predicted Gallons Plot[49]

After numerous iterations, no other predictor variables or interactions improve the adjusted R^2 of 0.853 and maintain significant *F* and *t*-tests. Table 3 reports the new table of statistics and shows that the *VIF* statistic for all six predictor variables are below five indicating that multicollinearity is no longer an issue. The *p*-value is greater than 0.05 for the *t*-test indicating that the intercept is insignificant. Therefore the final model is as follows:

$$Gallons_{millions} =$$

$$3.18(Combat\ Flying\ Hours_{thousands}) + 0.47(Training\ Flying\ Hours_{thousands}) -$$

$$20.37(C130H) + 12.33(F15C) - 28.33(T1A) + 18.51(Bomber\ \&\ Tankers)$$

Table 3: Final Single Macro-Level Table of Statistics[50]

Single Macro-Level Summary of Fit	
RSquare	0.85316
RSquare Adj	**0.85254**
Root Mean Square Error	12.28001
Mean of Response	12.01761
Observations (or Sum Wgts)	1422

Analysis of Variance (ANOVA)				
Source	**DF**	**Σ of Squares**	**μ Square**	**F Ratio**
Model	6	1239738.6	206623	1370.192
Error	1415	213380.0	151	**Prob > F**
C. Total	1421	1453118.6		**0.0000**

Parameter Estimates					
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**	**VIF**
Intercept	-0.37809	0.38645	-0.98	**0.3280**	--
Combat FH(K)	3.18419	0.04554	69.92	**0.0000**	**1.2083829**
Training FH (K)	0.46814	0.02261	20.7	**<.0001**	**1.3414849**
C-130H	-20.37252	2.14638	-9.49	**<.0001**	**1.0429436**
F-15C	12.33265	1.84898	6.67	**<.0001**	**1.0091182**
T-1A	-28.32668	4.55575	-6.22	**<.0001**	**1.2308578**
Bombers_Tankers	18.50742	1.10248	16.79	**<.0001**	**1.0751304**

The categorical predictors for the model are employed by inputting the counted number of MAJCOM representation by weapon system code (C-130H, F-15C, T-1A and Bombers/Tankers) that have programmed flying hours. The Bombers/Tankers categorical variable is still employed even if one of the weapon systems (B-1A, B-2B, B-52H, C-141B, C-

17A, C-5A/B/C, and KC-10A) has no flying hour representation. For example, if the C-141B no longer has programmed flying hours but the other five WSCs are all represented by three MAJCOMs, then the input for the Bombers/Tankers variable is 15. Before claiming the model useful to forecast the Air Force aviation fuel requirement, several diagnostics test are performed to ensure the assumptions of multiple linear regression are met.

<u>Single Macro-Level Model Statistical Significant Tests</u>

The regression model is sound if influential data points do not bias the selected explanatory variables and the tests for normality, constant variance, and independence are satisfied. Figure 9 displays the Cook's D influential statistic values on an overlay plot and reveals three influential data points. The 2006 and 2007 C-17A in Air Mobility Command (AMC) and the 2000 T-37B in the Air Education and Training Command (AETC) are the three influential data points. Although statistically influential, there are no logical reasons to exclude the three data points.

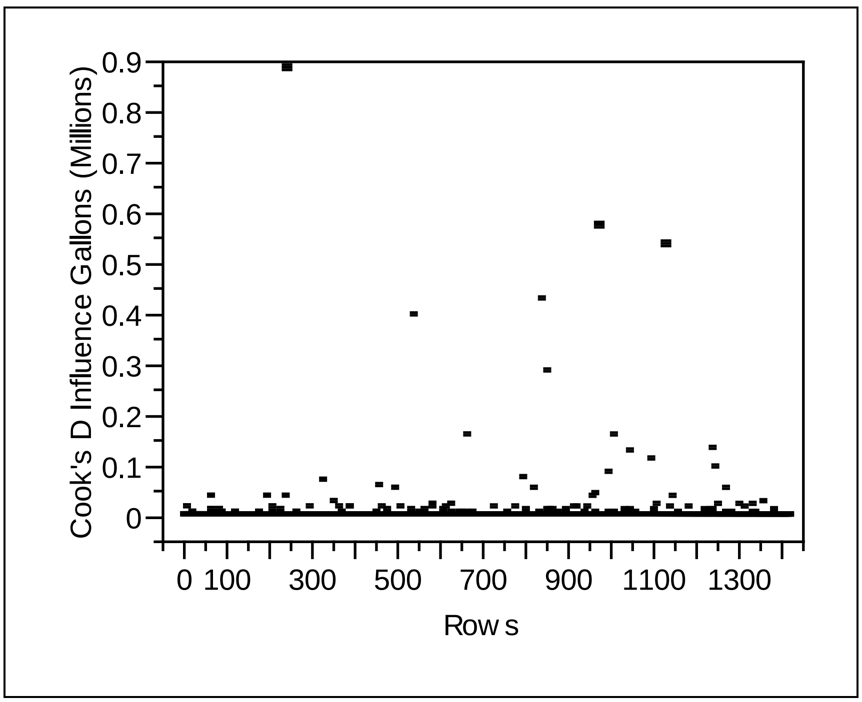

Figure 9: Single Macro-Level Model Test for Influential Data Points[51]

Figure 10 shows the gallons to flying hour relationship for the C-17A. The stars represent the 2006 and 2007 data points. There is no indication that the two C-17A data points are significantly different than the rest of the C-17A data with similar flying hours. Figure 11 shows that the C-17A from other MAJCOMs also follows along the same trend line.

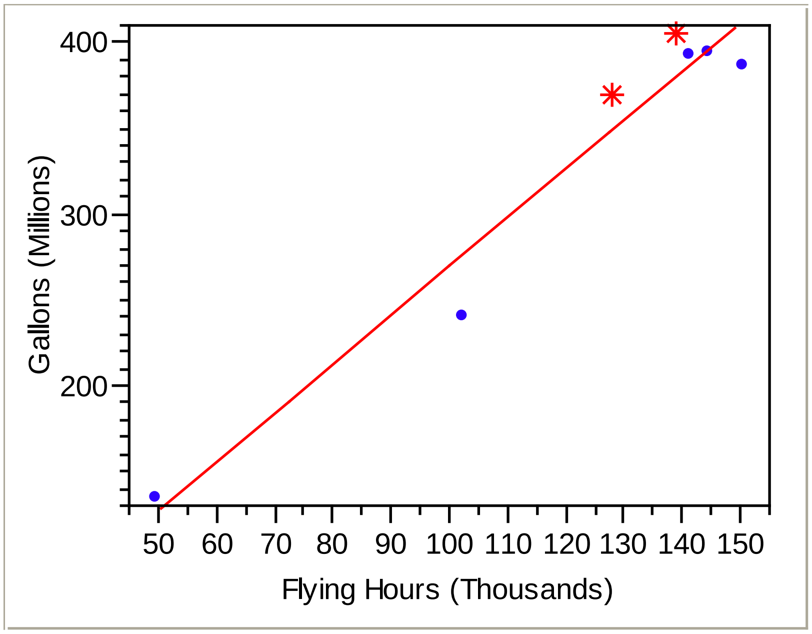

Figure 10: C-17A Gallons to Flying Hour Relationship for AMC[52]

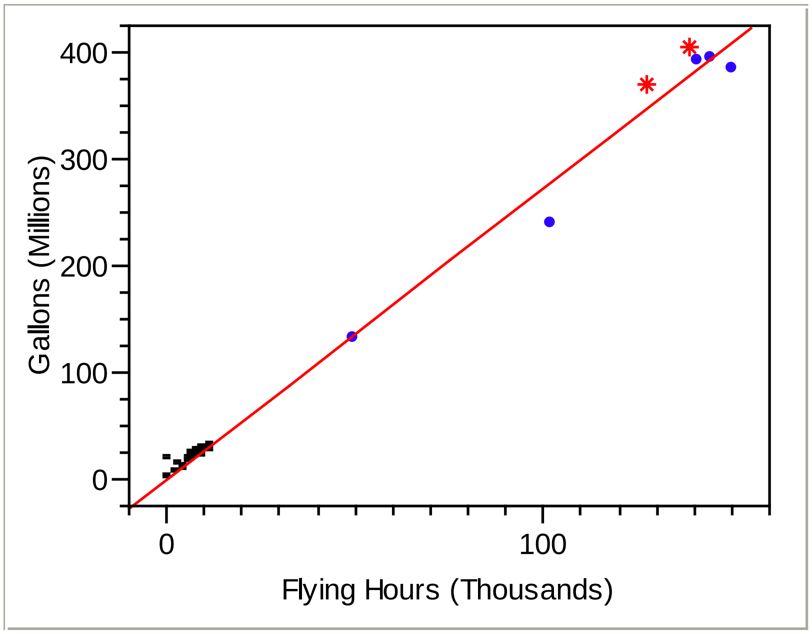

Figure 11: C-17A Gallons to Flying Hours Relationship across the Air Force[53]

The removal of data requires a sound explanation even if the Cook's D test indicates influential data. However, both Figure 10 and 11 illustrate that potential data entry errors are not plausible. Figure 12 shows a nearly perfect relationship between gallons and flying hours for the T-37B, indicating that the outliers are likely a result of flying more hours than the typical weapon system in the data. To remove the data would decrease the ability to effectively forecast the C-17A and T-37B fuel requirement.

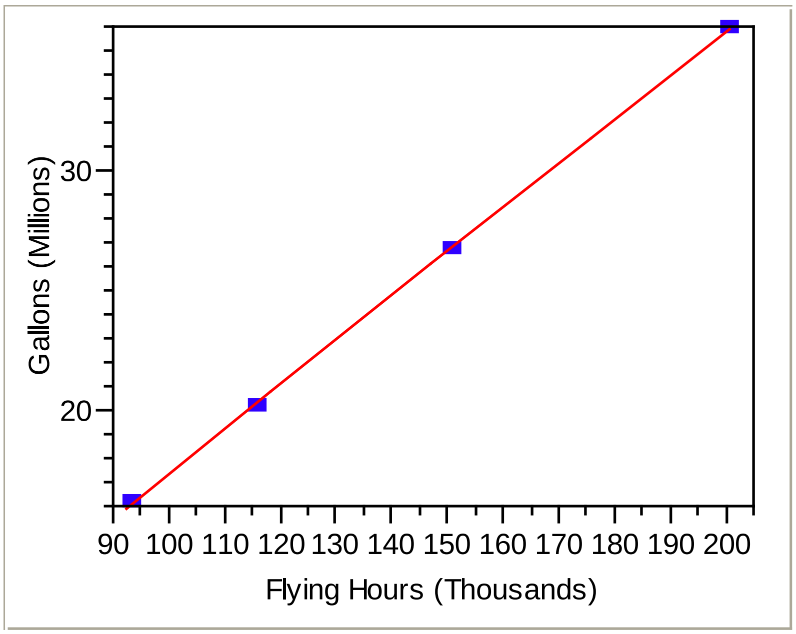

Figure 12: T-37B Gallons to Flying Hours Relationship for AETC[54]

The test for normality is determined by fitting a normal distribution about the residuals from the regression model. Figure 13 displays the residual distribution and the fitted normal function. The residuals are normally distributed when the *p*-value is greater than 0.05. The *p*-value of 0.00 indicates that the residuals are not normally distributed.

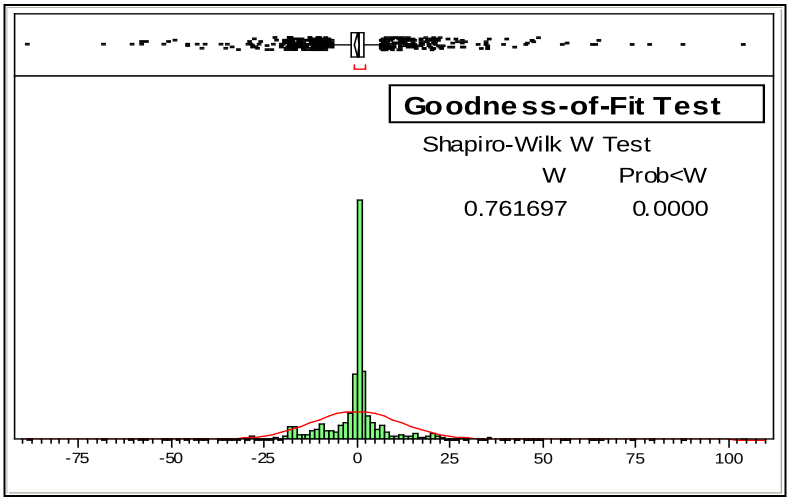

Figure 13: Single Macro-Level Model Normality Test[55]

The natural log transformation is often a solution to solving normality violations if a curve linear relationship exists. However, no curve linear relationship is evident in the data, thus the transformation did not correct the failure of normality. Although the linear regression model predicts a point estimate for gallons well, the point estimate variation inferences are based upon the assumptions of normality and constant variance. Thus, the range and probabilities associated with the variation of the model's prediction are not valid.

The tests for constant variance and independence are based upon an objective graphical view of the model residuals by the predicted gallons plot. The visual conclusion is that the assumption of constant variance and independence both fail. Figure 14 shows that the values for the residuals by predicted gallons are closely massed together with the minority fanning out. When constant variance and independence are present, the residuals are evenly distributed around the line 0. The failure of all three assumptions indicates that linear regression is not the model to predict aviation fuel requirements at the macro-level. However, the validation of the model's predictive capability is assessed and the potential for sub macro-level models are analyzed.

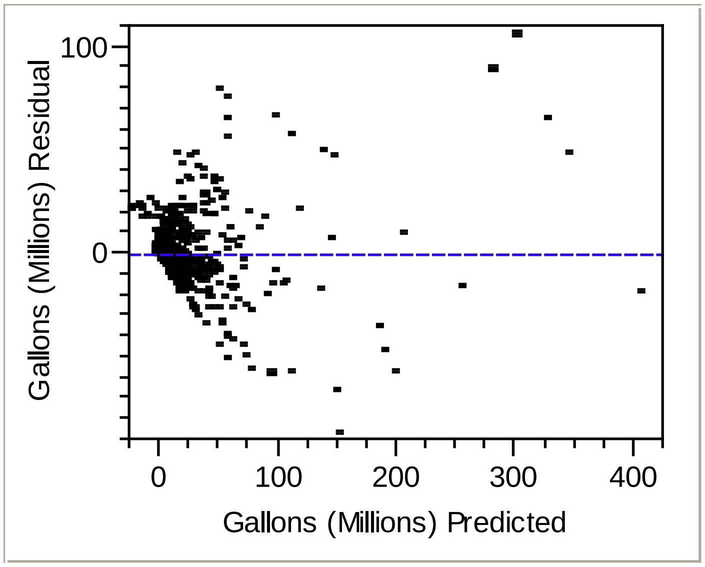

Figure 14: Single Macro-Level Model Test for Constant Variance[56]

<u>Single Macro-Level Aviation Fuel Regression Model Validation</u>

To validate the prediction capability of the single macro-level regression model, a random sample of 20 percent of the data was excluded from the original model development. The excluded data is fed into the regression model to compare the predictions to the actual gallons consumed. However, this validation is fundamentally flawed because the underlying assumptions of linear regression are not true. Thus, the 95% prediction or confidence intervals are theoretically faulty.

The difference between a prediction and confidence interval is important to understand. The confidence interval is the variation associated to the model's linear regression line. The prediction interval is the variation associated with any given predicted point estimate. The predictability of any single point is far more uncertain than the fitted regression line. For this reason, the prediction interval is always wider than the confidence interval. Typically, validation tests use a prediction interval because the focus is on individual points estimates.

The results are impressive but deceiving. Of the 356 point estimates, 100% fell within a 95 percent confidence interval and well within the 95 percent prediction interval. At the macro-

level, the model predicted a requirement of 4,428.27 million gallons versus the actual consumption of 4,486.18 million gallons, a difference of 57.91 million gallons, or only 1.29 percent. The lower and upper confidence levels are 3,998.79 and 4,857.75 millions of gallons respectively. The range of uncertainty defined by the 95 percent confidence interval (three standard deviations) is 856.96 millions of gallons or plus or minus 9.7 percent of the prediction.

The 95 percent prediction interval reveals the evidence of extreme or influential data points with a lower and upper bound of a negative 4,166.49 and 13,023.03 million gallons respectively. This equates to a range of 17,189 millions of gallons or plus or minus 194.1 percent of the prediction. The range of uncertainty is unrealistic and meaningless rendering a lack of confidence in the point estimate. The lower bound reveals the unrealistic nature of the model reporting a negative requirement for aviation fuel. Although the results are impressive, the single macro-level model application is discouraged without caution or understanding of the underlying statistics. For this reason, the research investigates potential sub macro-level models.

Sub Macro-Level Aviation Fuel Regression Models

The sub macro-level research attempts to group the data into like pools to alleviate the impact of influential data points and to satisfy the assumptions of linear regression. Figure 15 displays the same scatter plot shown in Figure 6, but identifies like sub-pooled groups of data. The same methodology is employed to each sub macro-level model and tested for the same underlying assumptions of linear regression.

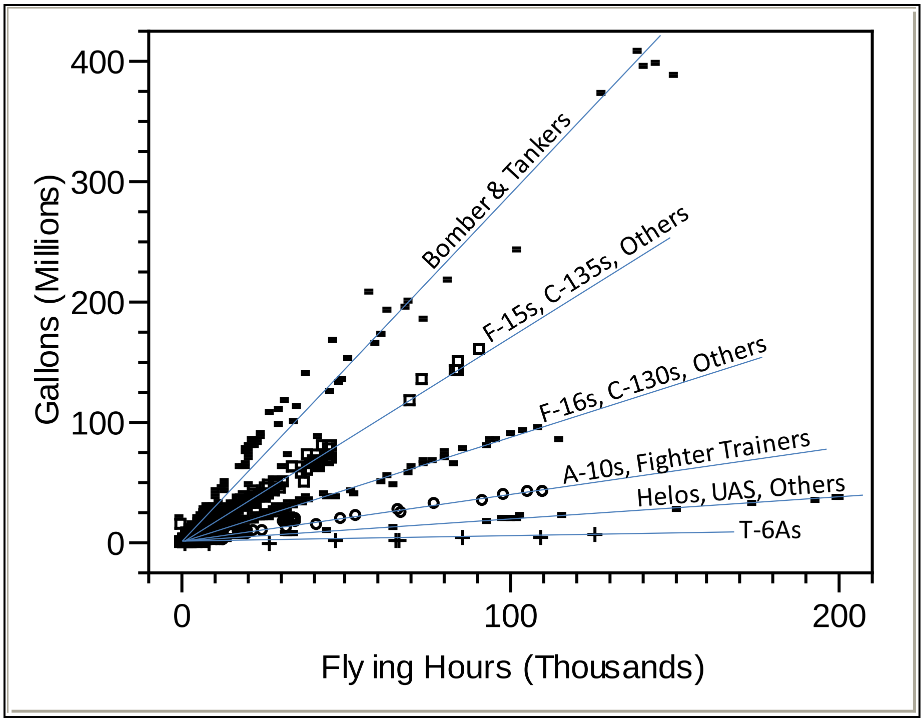

Figure 15: Scatter Plot Sub Macro-Level Pooled Data[57]

The Bomber and Tanker pooled group (B-1A, B-2B, B-52H, C-141B, C-17A, C-5A/B/C, and KC-10A) is the first set of data analyzed for a linear relationship. Figure 16 displays the relationship between gallons consumed and flying hours showing an initial concern with outliers, the massing of data at the lower gallons consumed, and the variation increasing as more hours are flown. The same concerns are prevalent in the single macro-level model. However, the test for a linear relationship and the theoretical assumptions are conducted to determine if the sub-level model is statistically significant.

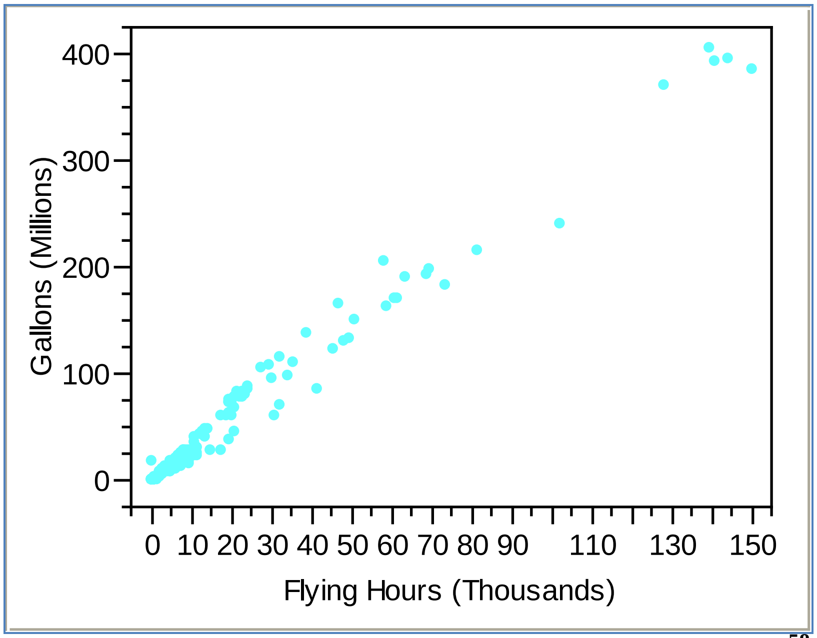

Figure 16: Scatter Plot of the Bomber and Tanker Group[58]

Figure 17 reports the least squares estimated gallons by the predicted gallons showing a strong relationship between gallons and flying hours with an adjusted R^2 of 0.986. Flying hours is the only significant explanatory variable when predicting gallons consumed explaining roughly 99 percent of the variation. The final Bomber and Tanker model is displayed as:

$$Gallons_{millions} = 2.54 + 2.75(Flying\ Hours_{thousands})$$

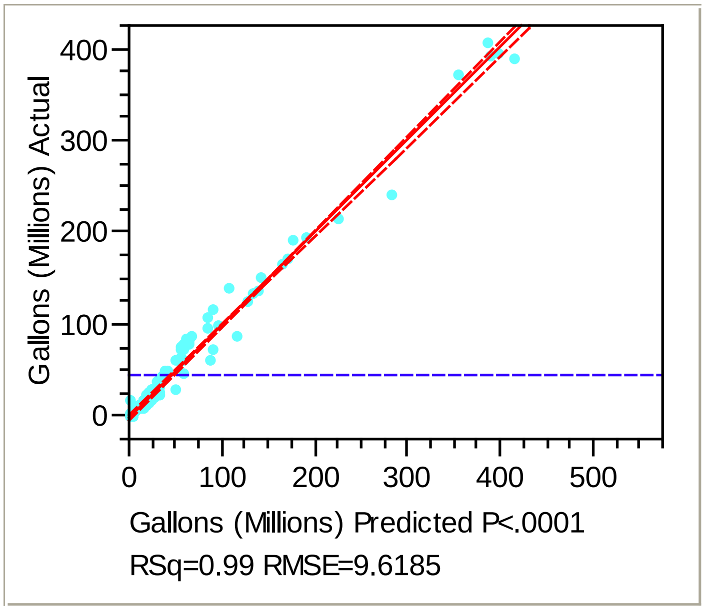

Figure 17: Bomber/Tanker Least Squares Estimated Gallons by Predicted Gallons Plot[59]

Table 4 displays the table of statistics with acceptable an *F*-test with a *p*-value less than 0.05 and the *VIF* less than five. Although the linear relationship is extremely strong, the theoretical assumptions of linear regression are tested for model soundness. The tests for influential data points, constant variance, independence, and normality follow.

Table 4: Bomber/Tanker Table of Statistics[60]

Single Macro-Level Summary of Fit					
RSquare					0.98567
RSquare Adj					**0.98557**
Root Mean Square Error					9.61852
Mean of Response					46.02283
Observations (or Sum Wgts)					149
Analysis of Variance (ANOVA)					
Source		**DF**	**Σ of Squares**	**μ Square**	**F Ratio**
Model		1	935233.8	935234	10108.9
Error		147	13599.8	93	**Prob > F**
C. Total		148	948833.7		**<0.0001**
Parameter Estimates					
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**	**VIF**
Intercept	2.5394719	0.898863	2.83	**0.0054**	--
Flying Hours (K)	2.7548227	0.027399	100.54	**<0.0001**	**1.0000**

Sub Macro-Level Model Statistical Significant Tests

Figure 18 reveals that the 2002 and 2003 C-17A in AMC are the two influential data points using Cook's D influential statistic values on an overlay plot. Although statistically influential, there are no logical reasons to exclude the two data points. The C-17A data is influential because of the higher flying hours and gallons consumed compared to the rest of the data set.

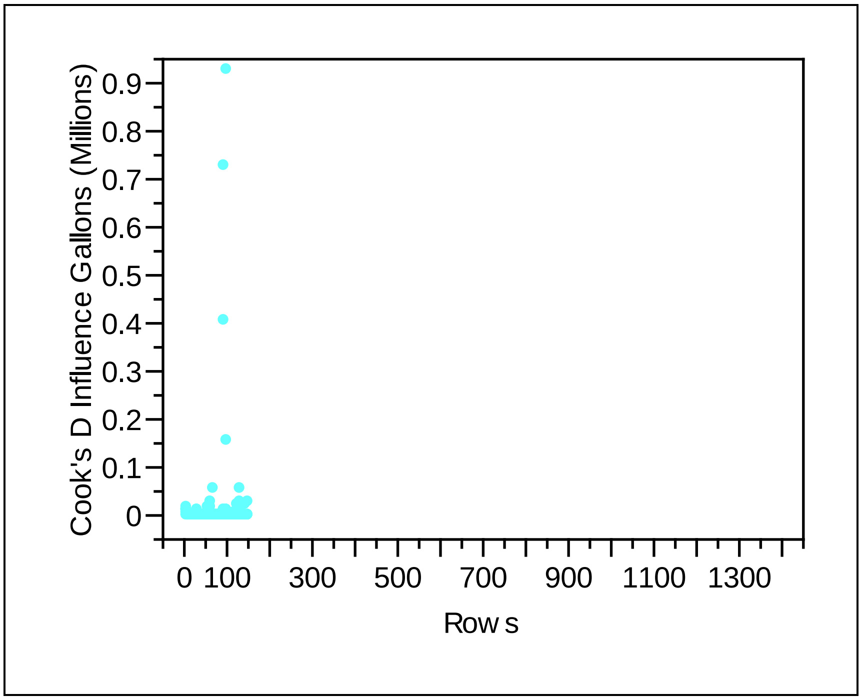

Figure 18: Bomber/Tanker Model Test for Influential Data Points[61]

When the influential data points are removed Table 5 shows insignificant change in the linear relationship or the parameter estimates. A significant improvement in the adjusted R^2 would indicate that the C-17A data is causing the "lone ranger effect" or regressing two significantly separate clusters of data. Essentially, regressing two different clusters of data is like regressing two data points. However, the adjusted R^2 drops 2.3 percent from 0.986 to 0.963 indicating that the C-17A data points have a small improvement effect on the linear relationship. The initial parameter estimate of 2.755 only drops to 2.749 when the two C-17A data point are

removed. The parameter estimates are virtually the same, indicating that the C-17A data falls on the same regression line as the majority of the data. Thus, the C-17A data should remain in the dataset.

Table 5: Bomber/Tanker Table of Statistics Excluding Influential Data Points[62]

Single Macro-Level Summary of Fit					
RSquare					0.96375
RSquare Adj					**0.96345**
Root Mean Square Error					9.23697
Mean of Response					34.06246
Observations (or Sum Wgts)					144
Parameter Estimates					
Term	**Estimate**	**Std Error**	**t Ratio**	**Prob>|t|**	**VIF**
Intercept	**2.5639255**	0.924818	2.77	**0.0063**	--
Flying Hours (K)	**2.7492339**	0.044742	61.45	**<0.0001**	**1.0000**

The test for normality is determined by fitting a normal distribution about the residuals from the Bomber and Tanker regression model. The residuals are normally distributed when the *p*-value is greater than 0.05. The *p*-value of 0.00 indicates that the residuals are not normal distributed displayed in Figure 19.

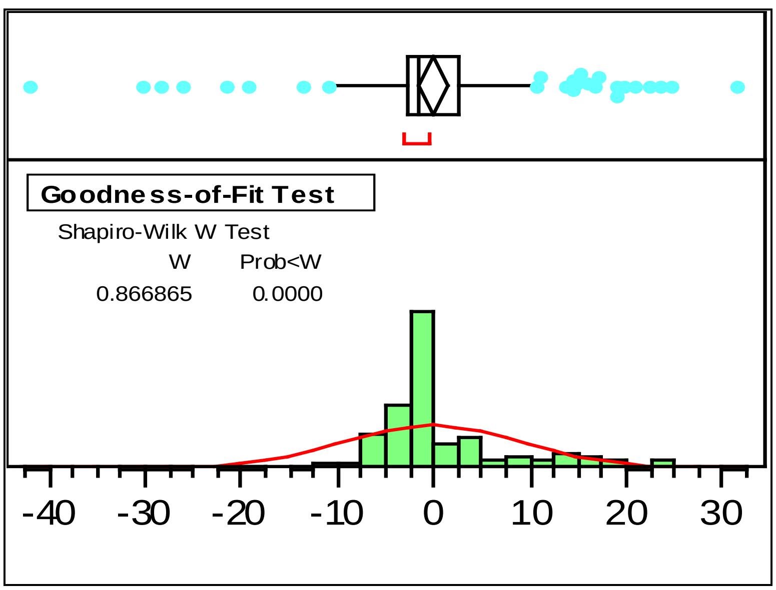

Figure 19: Bomber/Tanker Macro-Level Model Normality Test[63]

Based upon an objective graphical view of the Bomber and Tanker model residuals by the predicted gallons plot in Figure 20, the visual conclusion is that the assumption of constant variance and independence both fail. The residuals should follow an even distribution about the line 0 across both the x and y axis. However, Figure 20 clearly shows the majority of the data is gathered at the lower end of the gallons predicted scale and then fans out abruptly. Like the single macro-level model, the sub macro-level model does not solve the linear regression assumption failures of normality, constant variance, and independence. Therefore, the variation inferences derived from linear regression are faulty. However, the linear regression model is highly accurate at predicting gallons consumed as shown in the Bomber and Tanker model validation.

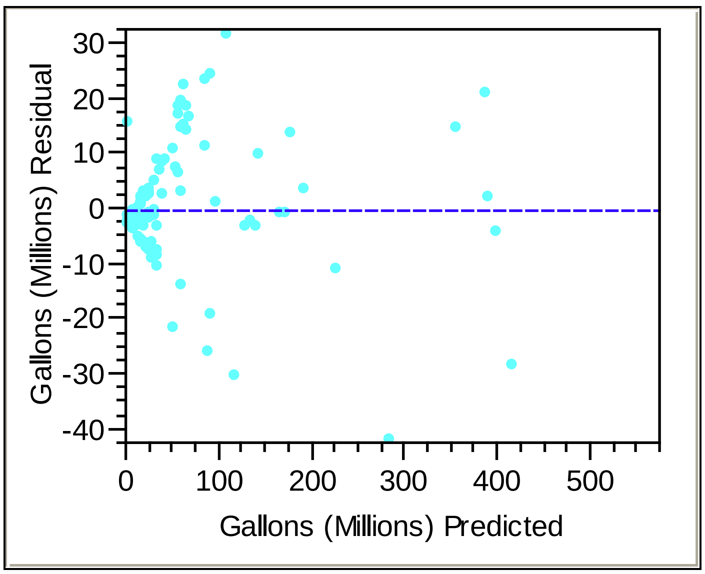

Figure 20: Bomber/Tanker Model Test for Constant Variance[64]

Sub Macro-Level Aviation Fuel Regression Model Validations

The same single macro-level model methodology is employed to validate the prediction capability of the Bomber and Tanker sub macro-level regression model. Like the single macro-level model, validation is fundamentally flawed because the underlying assumptions of linear

regression are not true. However, the results are provided to show the predictive capability of the Bomber and Tanker model.

Again, the results are impressive but deceiving. Of the 42 point estimates, 100% fell within a 95 percent confidence interval and well within the 95 percent prediction interval. At the macro-level, the model predicted a requirement of 1,732.03 million gallons versus the actual consumption of 1,817.47 million gallons, a difference of 85.44 million gallons or only 4.70 percent. The lower and upper confidence levels are 1,655.14 and 1,808.91 millions of gallons respectively. The range of uncertainty defined by the 95 percent confidence interval (three standard deviations) is 153.77 millions of gallons or plus or minus 4.4 percent of the prediction.

The 95 percent prediction interval reveals the evidence of extreme or influential data points with a lower and upper bound of 929.77 and 2,534.29 million gallons respectively. This equates to a range of 1,604.51 millions of gallons or plus or minus 46.3 percent of the prediction. The range of uncertainty is unrealistic and meaningless indicating a lack of confidence in point estimate predictions. Although the linear relationship is impressive, the Bomber and Tanker sub macro-level model application is discouraged without caution or understanding of the underlying statistics.

Table 6 reports a summarized table of the six sub macro-level models and the single macro-level model. The remaining five sub macro-level models have strong linear relationship but fail the theoretical assumptions of linear regression. Appendix B displays the graphical linear regression assumption test results of all six sub macro-level models. The single macro-level model predicted the actual aviation fuel gallons consumed better than the summation of the six sub macro-level models. However, the variation of the single macro-level model is over four

times wider than the sub macro-level model. Both models are potentially useful to provide secondary estimates to aviation fuel requirements.

Table 6: Summary of Linear Regression Models

Description of Data	Sub Model[1]	Sub Model[2]	Sub Model[3]	Sub Model[4]	Sub Model[5]	Sub Model[6]	Σ of Sub Macro	Single Macro
Number of Observations Withheld	42	105	133	1	42	33	356	356
Actual Aviation Fuel Consumed	1,817.47	958.81	1,405.53	2.20	140.32	161.85	4,486.18	4,486.18
Predicted Aviation Fuel Consumed	1,732.03	782.30	1,377.67	1.73	150.56	154.28	4,198.58	4,428.27
Actual - Predicted Gallons	85.44	176.51	27.86	0.46	(10.24)	7.56	287.60	57.91
Percent Difference of Actual and Predicted	4.70%	18.41%	1.98%	21.14%	-7.30%	4.67%	6.41%	1.29%
Lower Bound of 95% Confidence Interval (CI)	1,655.14	760.60	1,340.49	1.71	146.34	145.01	4,049.30	3,998.79
Upper Bound of 95% CI	1,808.91	804.00	1,414.86	1.75	154.78	163.56	4,347.86	4,857.75
95% CI Range	153.77	43.39	74.38	0.04	8.44	18.54	298.56	858.96
95% CI +/- 3σ	4.44%	2.77%	2.70%	1.05%	2.80%	6.01%	3.56%	9.70%
Lower Bound of 95% Prediction Interval (PI)	929.77	429.08	721.96	1.69	110.74	51.24	2,244.48	(4,166.49)
Upper Bound of 95% PI	2,534.29	1,135.52	2,033.39	1.78	190.37	257.33	6,152.67	13,023.03
95% PI Range	1,604.51	706.44	1,311.44	0.09	79.63	206.09	3,908.19	17,189.51
95% PI +/- 3σ	46.32%	45.15%	47.60%	2.46%	26.45%	66.79%	46.54%	194.09%
Regression Statistics								
Ajusted R^2	0.986	0.987	0.983	0.999	0.992	0.971	NA	0.853
Variance Inflation Factor (VIF)	Pass	Pass	Pass	Pass	Pass	Pass	NA	Pass
F-test	Pass	Pass	Pass	Pass	Pass	Pass	NA	Pass
t-test	Pass	Pass	Pass	Pass	Pass	Pass	NA	Pass
Cook's D Test for Infuential Data Points	Fail[7]	Fail[8]	Fail[9]	Pass	Fail[10]	Fail[11]	NA	Fail[12]
Test for Normality	Fail	Fail	Fail	Pass	Fail	Fail	NA	Fail
Constant Variance/Independence	Fail	Fail	Fail	Unknown	Fail	Fail	NA	Fail
Number of Observations	149	403	534	8	181	147	NA	1422

Weapon System Code (WSC) Breakout for each Sub Macro-Level Model:

1. Bomber and Tanker Sub Macro-Level Model (B-1A, B-2B, B-52H, C-141B/C, C-17A, C-5A/B/C, KC-10A)
2. F-16 and C-130 Sub Macro-Level Model (AC-130H/U, C-130E/H/J, EC-130E/H, F-117A, F-16A/B/C/D, HC-130N/P, LC-130H, MC-130E/H/P, NC-130H, TC-130H, WC-130H)
3. F-15 and C-135 Sub Macro-Level Model (C-12C/F/J, C-135B/C/E, C-20A/B, C-22B, C-26A/B, C-32A/B, C-37A, C-38A, C-40B/C, C-9A/C, E-3B/C, E-4B, E-8C, EC-135K/N, F-15A/B/C/D/E, F-22A, KC-135D/E/R/T, NKC-135E, OC-135B, RC-135U/V/W, TC-135S, TE-8A, VC-25A, WC-135C)
4. T-6 Sub Macro-Level Model (T-6A)
5. Helo and UAS Sub Macro-Level Model (C-21A, HH-60G, MH-53M, MQ-9A, RQ-9A, T-37B, U-2S, UH-1N/V)
6. A-10 Sub Macro-Level Model (A-10A, OA-10A, AT-38B, F-4F, T-38A/C, T-39B)

Other Notes:

7. Influencial data point causes only slight change in linear regression model's slope and intercept
8. Influencial data point causes only slight change in linear regression model's slope and intercept
9. Influencial data point causes only slight change in linear regression model's slope and intercept
10. Influential data produces "lone ranger" affect potentially changing the linear regression model slope and intercept
11. Influencial data point causes only slight change in linear regression model's slope and intercept
12. Influencial data point causes only slight change in linear regression model's slope and intercept

The Six Sub Macro-Level Linear Regression Models (Use WSC breakout flying hour totals):	**Colors**
1. $\text{Gallons}_{\text{Millions}} = 2.5394719 + 2.7548227\ (\text{Flying Hours}_{\text{Thousands}})$	Light Blue
2. $\text{Gallons}_{\text{Millions}} = -0.161457 + 0.8335911\ (\text{Flying Hours}_{\text{Thousands}})$	Yellow
3. $\text{Gallons}_{\text{Millions}} = -0.29016 + 1.7213995\ (\text{Flying Hours}_{\text{Thousands}})$	Green
4. $\text{Gallons}_{\text{Millions}} = -0.002574 + 0.0652076\ (\text{Flying Hours}_{\text{Thousands}})$	Black
5. $\text{Gallons}_{\text{Millions}} = -0.077913 + 0.1846358\ (\text{Flying Hours}_{\text{Thousands}})$	Red
6. $\text{Gallons}_{\text{Millions}} = 0.9833719 + 0.419244\ (\text{Flying Hours}_{\text{Thousands}})$	Blue

The failure of the theoretical assumptions indicates that linear regression is not the ideal method to forecast aviation fuel requirements. Although the sub and single macro-level models predict the actual gallons consumed well, the forecasted point estimate is highly uncertain due to the failure of fundamental linear regression assumptions. Further analysis was conducted to separate the data into categories according to the number of flying hours. This produced favorable results for weapon systems that flew over 10 million hours, producing a statistically significant model that met linear regression assumptions. However, the model proved incomplete as the lower flying hour data points did not realize statistically significant models or pass the linear regression assumptions. Thus, pooling time series data to employ linear multiple regression is not the preferred model building method to forecast aviation fuel requirements.

Chapter Summary

This chapter provides the results of applying the methodology to 1,778 pooled data points of gallons consumed by weapons systems. The methodology is applied first to a single macro-level model which perfectly predicts gallons within a 95 percent confidence interval. However, the underlying assumptions of the single macro-level linear regression model are faulty. For this reason, the data is divided into sub-pooled sets and the methodology is reapplied. The sub macro-level models also perfectly predict gallons within a 95 percent confidence interval. Unfortunately, the sub macro-level model also suffers from the same shortcomings, failing the tests of normality, constant variance, and independence. Although both models prove valid as capable prediction models based upon a 95 percent prediction and confidence interval, the statistics that provide the basis for the variation calculations are not founded upon sound linear regression assumptions. Thus, the application of the single and sub macro-level linear

relationship models application is discouraged without caution or understanding of the underlying statistics. Chapter Five summarizes and concludes this research effort.

V. Conclusion

Chapter Overview

This chapter summarizes the findings and conclusions of developing a model to forecast aviation fuel requirements using pooled times series analysis. Chapters One, Two, and Three are summarized and a summary of the results of Chapter Four are presented. Finally, the limitations of this research are presented and recommendations are provided for future research efforts.

Research Summary

Chapter One introduces the AFCAA search for a macro-level model that will forecast the United States Air Force (USAF) aviation fuel requirement. The AFCAA would like a macro-level model that will provide a cross-check to current aviation fuel estimates or potentially replace the current technique employed. In the wake of volatile aviation fuel prices and the USAF's dependency on foreign oil, a macro-level model will provide the AFCAA with a forecasting model to conduct alternative fuel source comparisons. The chapter concludes with the AFCAA desire for this research to determine if pooled time series analysis can develop a macro-level model to forecast the baseline Air Force aviation fuel requirement for alternative fuel source comparison studies.

Chapter Two describes the United States and USAF's dependency on foreign oil and the vulnerabilities associated when competing for a global finite resource. A brief summary of potential alternative fuel sources are reviewed. The chapter then focuses on existing methods or techniques to forecast aviation fuel requirements. Finally, the Coast Guard's pooled time series analysis ship and aviation forecasting model is examined for applicability to forecasting Air Force aviation fuel requirements.

Chapter Three describes the pooled time series analysis methodology used by the Coast Guard to develop mathematical relationships to forecasts aviation and ship fuel requirements. An explanation of the data preparation and pooling technique is provided. The chapter introduces the potential explanatory variables used in the regression analysis, and describes the theoretical tests necessary to claim a statistically significant model. The chapter continues by explaining the methodology used to validate the predictive capability of a theoretically sound model. Finally, the method to assess the risk and uncertainty of model predictions is explained.

Chapter Four presents the results of the pooled times series analysis methodology applied to 1,778 pooled data points of gallons consumed by weapons systems. Two models are developed and explained. The first is the single macro-level model which perfectly predicts gallons within a 95 percent confidence interval. The second is the sub macro-level model which also perfectly predicts gallons within a 95 percent confidence interval. The chapter explains that both models predicted actual historical consumption well, however, both model's failed the underlying assumptions of linear regression. For this reason, the single and sub macro-level linear relationship models application is discouraged without caution or understanding of the underlying statistics.

Model Application and Limitations

The application of either the single or sub macro-level model to forecast aviation fuel requirements is discouraged. Both models suffer from the same statistical limitations in that the underlying assumptions of linear regression are violated. However, applying the models as a cross-check to current aviation fuel requirement estimates will provide another layer of validation to the both model's predictive capability.

Future Research

The research indicates that linear multiple regression, even when pooling the data, is not the best method to develop a macro-level aviation fuel requirements model. Further analysis to find better explanatory variables may produce favorable results using linear regression. As stated earlier in Chapter Two, the AFCAA's 1998 fuel consumption cost estimating relationship study reveals other possible explanatory variables that may better predict aviation fuel consumption when employing pooled times series analysis. Future investigations of other potential methodologies are worth researching such as maximum likelihood regression or non-linear estimation techniques.

Conclusions

This research developed a macro-level model that predicted aviation fuel requirements well using a pooled time series analysis methodology. The validation tests proved impressive as the model predicted historical gallons consumed 100 percent of the time within a 95 percent confidence and prediction interval. The results are impressive but deceiving for two major reasons.

First, although the macro-level regression model predicts historical aviation fuel requirements well, the theoretical assumptions for linear regression fail. The underlying linear regression assumptions of normality, constant variance, and independence are the foundation to a statistically significant liner regression model. The macro-level model fails the three assumptions, thus bringing into question the accuracy of individual predictions for future gallon consumption requirements. Although the validation tests report that the models predict historical gallons consumed 100 percent of the time within a 95 percent confidence and prediction interval, both intervals are based upon the same test failures essential to linear regression. Thus, the

validation results are fundamentally faulty. The research investigated the potential of breaking the macro-level pooled data into sub macro-levels to correct for the linear regression assumption failures. However, the sub macro-level models revealed the same theoretical failures indicating that linear regression is not the ideal methodology to develop a model to predict aviation fuel requirements.

Second, the confidence and prediction intervals provide the basis to conduct uncertainty and risk analysis. However, the standard deviation or variance statistics that determine the intervals are only valid if the fundamental assumptions of linear regression are satisfied. Thus, using the mean and standard deviation parameters for a Monte Carlo simulation to determine the quantitative uncertainty or risk in the models predictions is fundamentally flawed. Therefore, the research concludes that the application of either the single or sub macro-level models is discourage without proper understanding of the underlying statistics provided.

Appendix A: Categorical Predictors

Table 7: Detailed List of Categorical Predictors

Weapon System Codes (WSC)									
1	A-10A	20	C-20A	39	E-4B	58	HC-130P	77	RC-135W
2	AC-130H	21	C-20B	40	E-8C	59	HH-60G	78	RQ-4A
3	AC-130U	22	C-21A	41	EC-130E	60	KC-10A	79	T-37B
4	AT-38B	23	C-22B	42	EC-130H	61	KC-135D	80	T-38A
5	B-1B	24	C-26A	43	EC-135K	62	KC-135E	81	T-38C
6	B-2A	25	C-26B	44	EC-135N	63	KC-135R	82	T-39B
7	B-52H	26	C-32A	45	F-117A	64	KC-135T	83	T-6A
8	C-12C	27	C-32B	46	F-15A	65	LC-130H	84	TC-130H
9	C-12F	28	C-37A	47	F-15B	66	MC-130E	85	TC-135S
10	C-12J	29	C-38A	48	F-15C	67	MC-130H	86	TE-8A
11	C-130E	30	C-40B	49	F-15D	68	MC-130P	87	U-2S
12	C-130H	31	C-40C	50	F-15E	69	MH-53M	88	UH-1N
13	C-130J	32	C-5A	51	F-16A	70	MQ-9A	89	UH-1V
14	C-135B	33	C-5B	52	F-16B	71	NC-130H	90	VC-25A
15	C-135C	34	C-5C	53	F-16C	72	NKC-135E	91	WC-130H
16	C-135E	35	C-9A	54	F-16D	73	OA-10A	92	WC-135C
17	C-141B	36	C-9C	55	F-22A	74	OC-135B		
18	C-141C	37	E-3B	56	F-4F	75	RC-135U		
19	C-17A	38	E-3C	57	HC-130N	76	RC-135V		

Major Commands (MAJCOMs)		**Mission Type**	
1	Air Combat Command (ACC)	1	Bombers
2	Air Education and Training Command (AETC)	2	Fighters
3	Air Force Materiel Command (AFMC)	3	Command and Control
4	Air Force Reserve Command (AFRC)	4	Combat Search & Rescue
5	Air Force Space Command (AFSPC)	5	Electronic Warfare
6	Air Force Special Operations Command (AFSOC)	6	ISR
7	Air Mobility Command (AMC)	7	Special Operations
8	Air National Guard (ANG)	8	Strategic Lift
9	Pacific Air Force (PACAF)	9	Tactical Lift
10	United State Air Force in Europe (USAFE)	10	Tanker
		11	Trainer

Weapon System Type	
1	Bombers
2	Fighters
3	Helicopters
4	Reconnaissance
5	Special Duty
6	Trainers
7	Tanker Transport
8	Unmanned Aerial Systems

Appendix B: Statistical Tests for the Sub Macro-Level Models

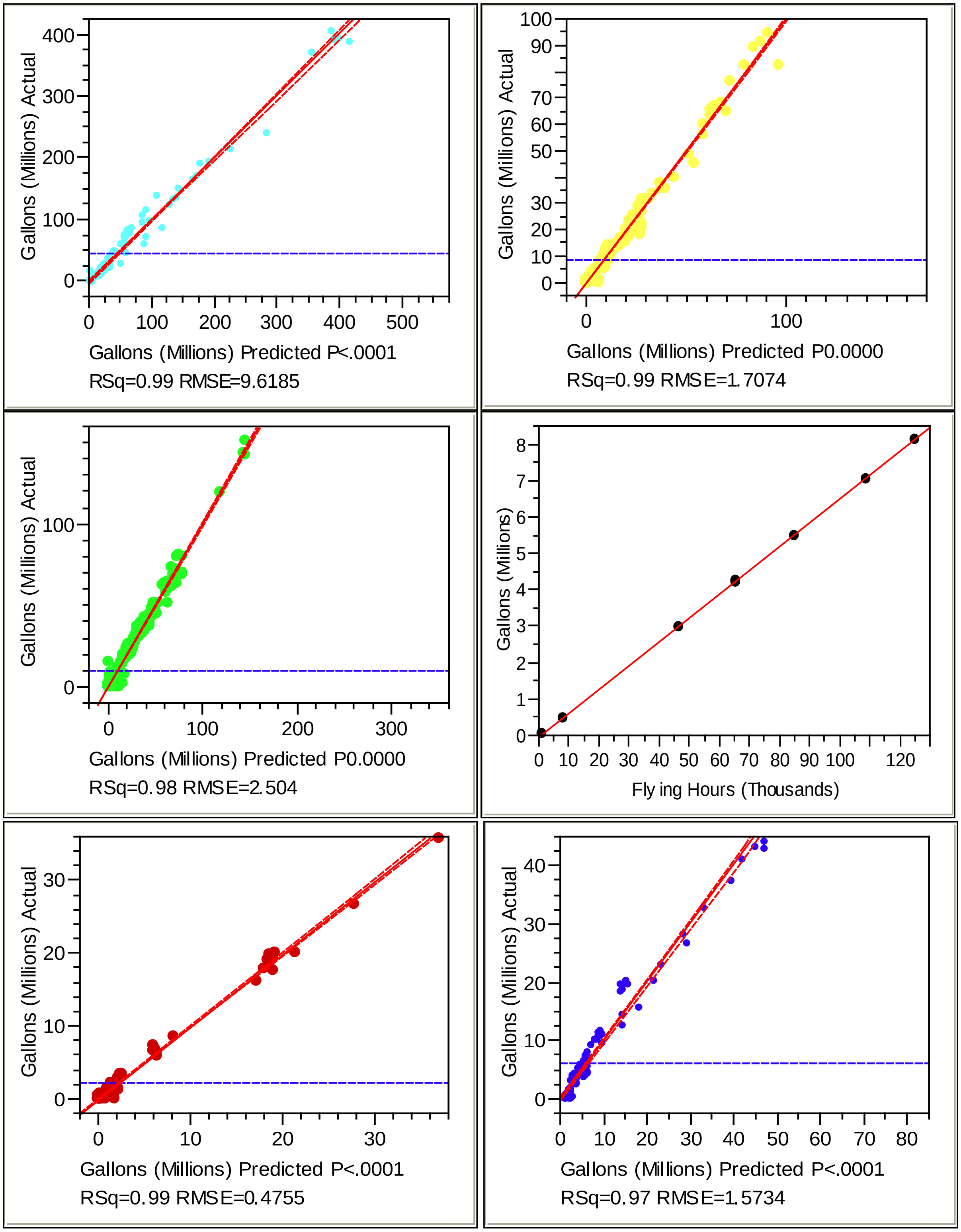

Figure 21: Sub Macro-Level Models Predicted by Actual Gallons Plot[65]

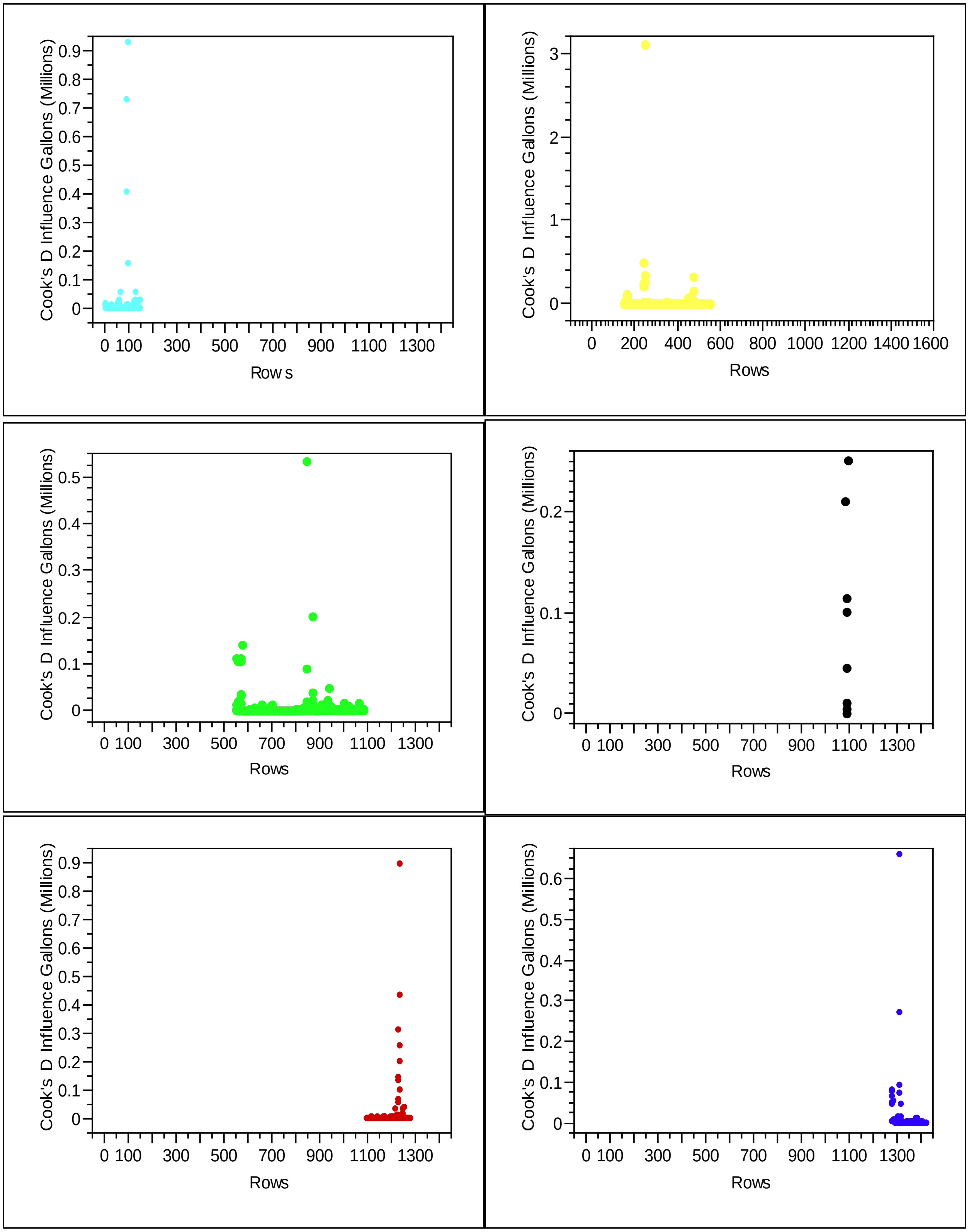

Figure 22: Sub Macro-Level Models Test for Influential Data Points[66]

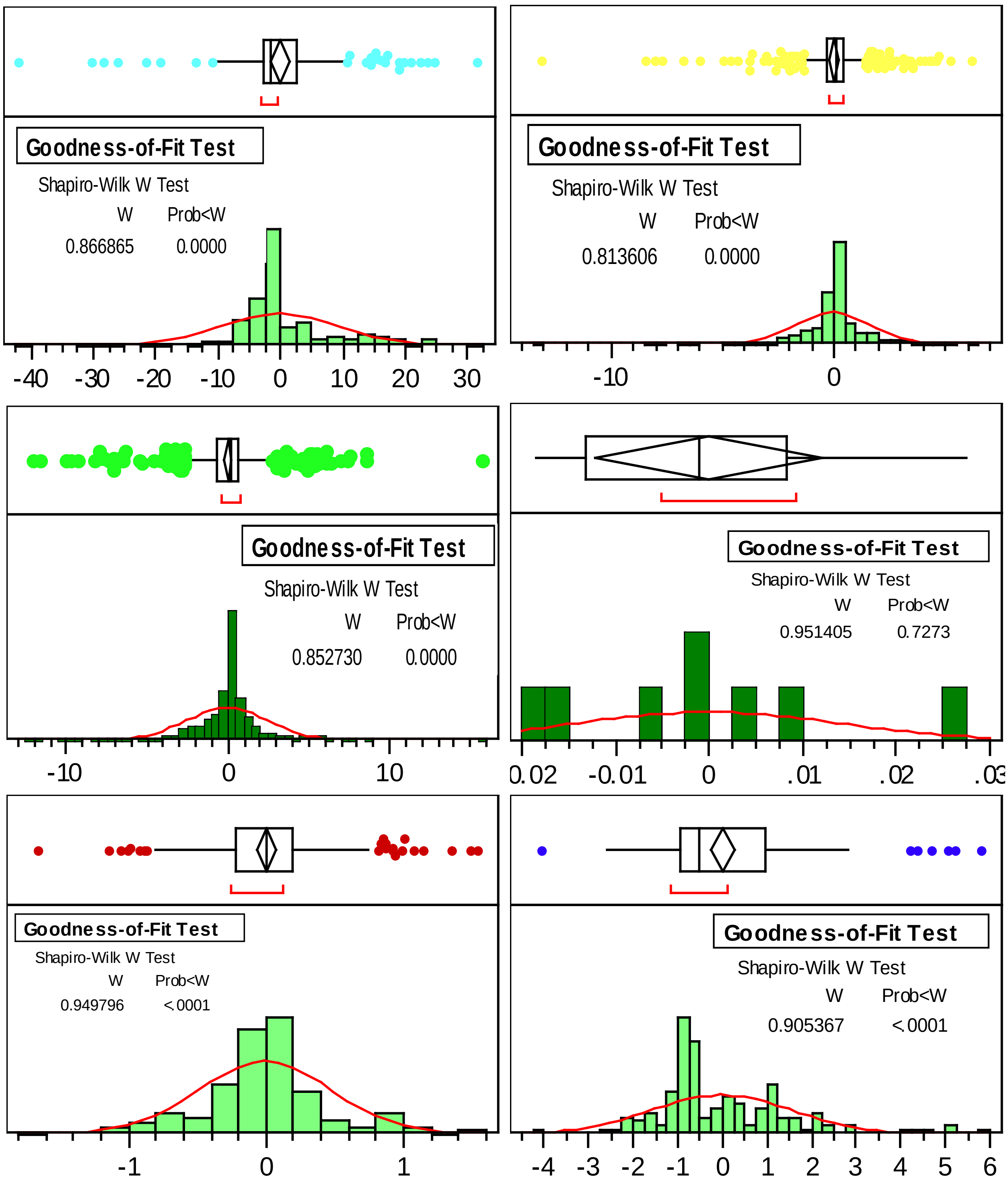

Figure 23: Sub Macro-Level Models Test for Normality[67]

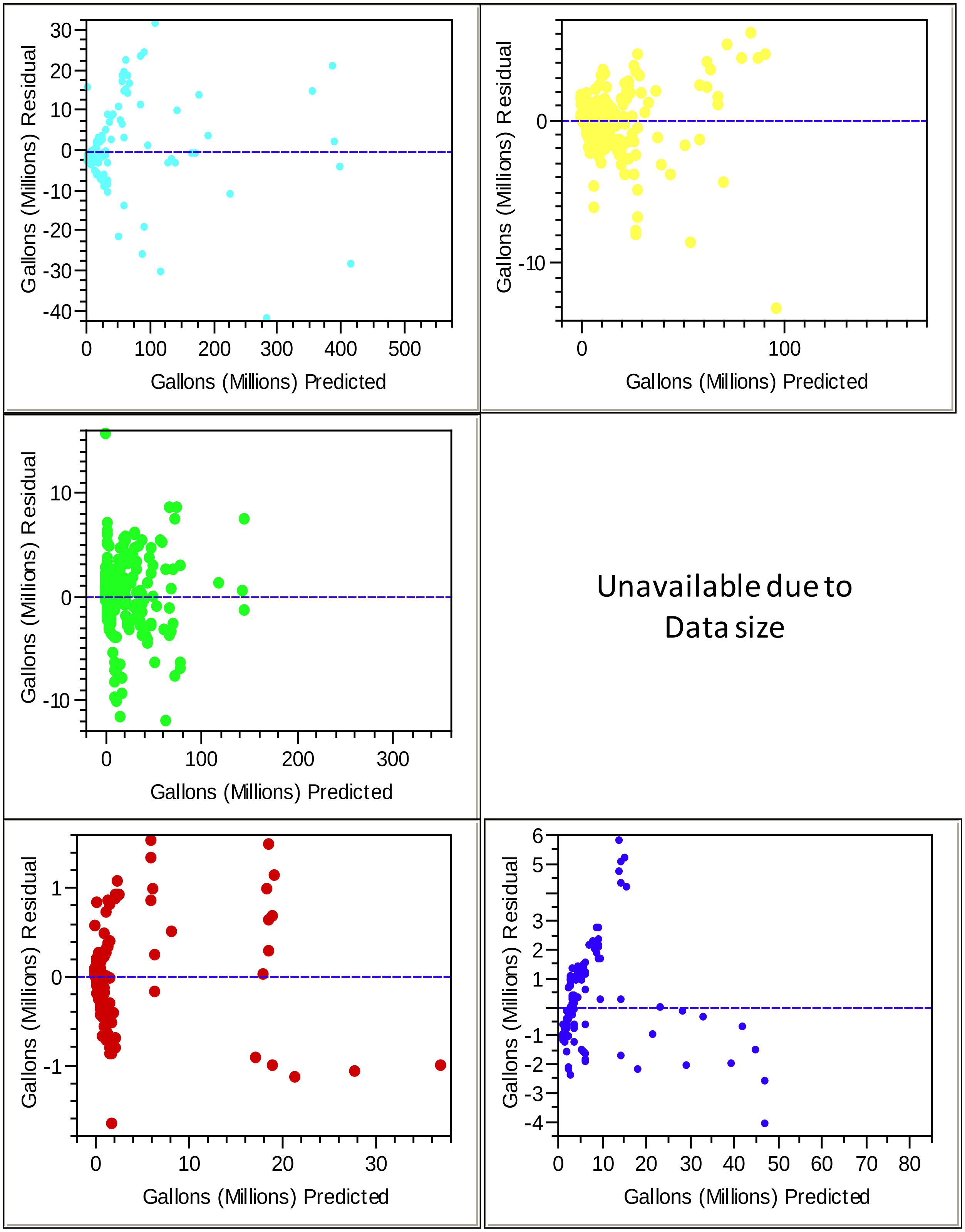

Figure 24: Sub Macro-Level Models Test for Constant Variance[68]

Appendix C: Correlation Matrix for Macro-Level Model

Table 8: Correlation Matrix for Predictor Variables[69]

Correlation Maxtrix	Combat FH(K)	Training FH(K)	Total Sorties	C-130H	F-15C	T-1A	Bombers/ Tankers
Combat FH(K)	**1.000**	0.278	0.296	0.171	(0.018)	(0.014)	0.233
Training FH(K)	0.278	**1.000**	0.960	0.079	0.044	0.410	0.006
Total Sorties	0.296	**0.960**	**1.000**	0.099	0.064	0.247	(0.038)
C-130H	0.171	0.079	0.099	**1.000**	(0.029)	(0.013)	(0.054)
F-15C	(0.018)	0.044	0.064	(0.029)	**1.000**	(0.015)	(0.063)
T-1A	(0.014)	0.410	0.247	(0.013)	(0.015)	**1.000**	(0.027)
Bombers_Tankers	0.233	0.006	(0.038)	(0.054)	(0.063)	(0.027)	**1.000**

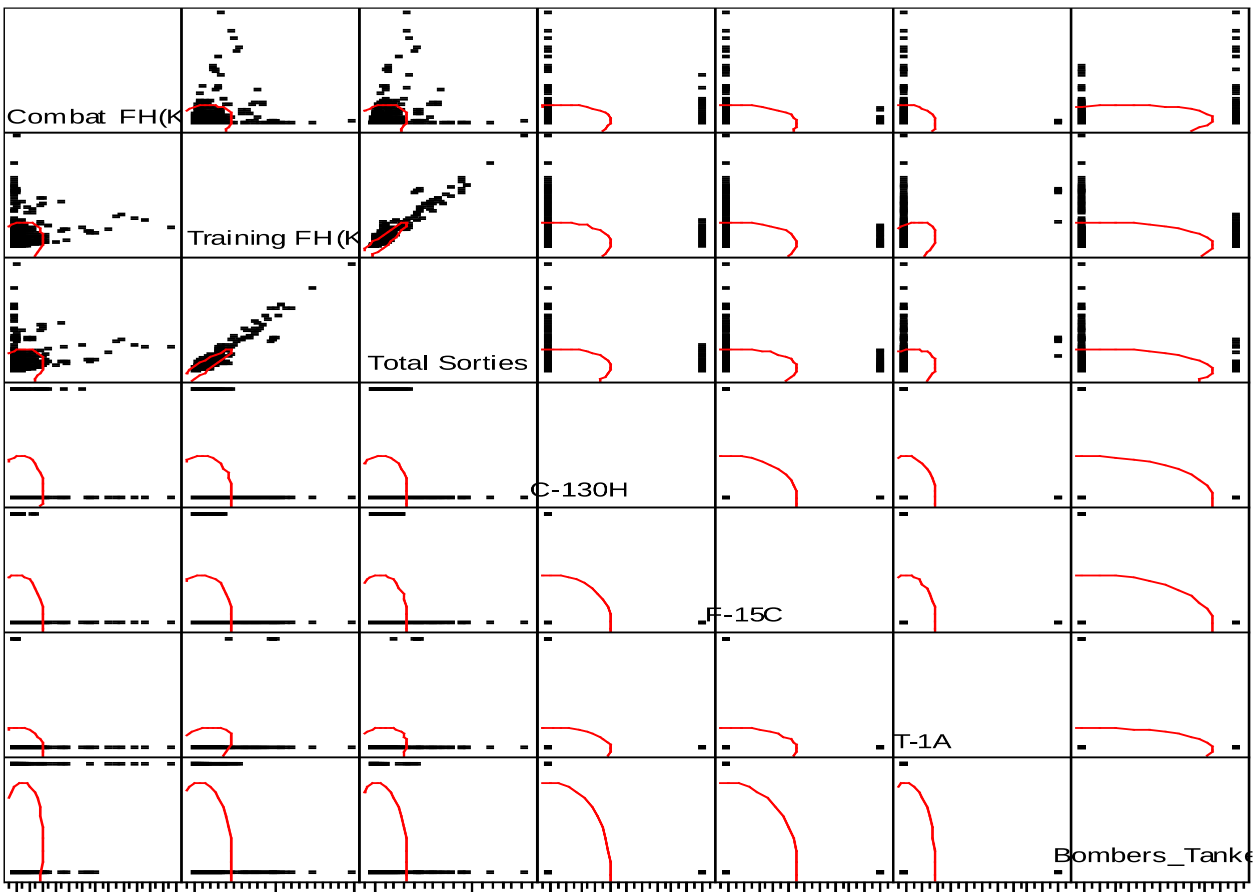

Figure 25: Macro-Level Model Correlation Matrix Scatter Plot[70]

Notes

[1]CIA World Fact Book.
[2] Ibid.
[3] Petersen, The Road to 2015, 146.
[4] EIA, 2008.
[5] Myers, Ultimate Security, 177.
[6] Roberts, The End of Oil, 57.
[7] EIA, 2008.
[8] Ibid.
[9] Roberts, The End of Oil, 51.
[10] Ibid, 52.
[11] Ibid, 52.
[12] Ibid, 59.
[13] CIA World Fact Book.
[14] US Census Bureau.
[15] Air Force Cost Analysis Agency, Thomas Lies.
[16] CIA World Fact Book.
[17] Danigole, 1.
[18] Ibid, 9.
[19] Ibid, 4.
[20] Ibid, 4.
[21] Ibid, 6.
[22] Ibid, 25-29.
[23] AFCAA. Fuel Consumption Cost Estimating Relationship, 2-4.
[24] Schwartz, Forecasting Fuel Consumption, 1-1.
[25] Ibid, 2-3.
[26] Ibid, A-1.
[27] Ibid, A-1.
[28] Ibid, 2-3.
[29] Ibid, A-2, A-3.
[30] Sall, JMP Start Statistics Software.
[31] Ibid.
[32] Brown, Forecasting Research & Development Program Budgets, 36.
[33] Ibid, 44.
[34] Sall, JMP Start Statistics Software.
[35] Neter, Applied Linear Statistical Models, 380.
[36] Sall, JMP Start Statistics Software.
[37] Neter, Applied Linear Statistical Models, 115.
[38] Brown, Forecasting Research & Development Program Budgets, 45.
[39] Ibid, 45.
[40] Ibid, 46.
[41] Sall, JMP Start Statistics Software.

[42] Brown, Forecasting Research & Development Program Budgets, 51.
[43] Sall, JMP Start Statistics Software.
[44] Ibid.
[45] Ibid.
[46] Neter, Applied Linear Statistical Models, 385.
[47] Ibid, 387.
[48] Sall, JMP Start Statistics Software.
[49] Ibid.
[50] Ibid.
[51] Ibid.
[52] Ibid.
[53] Ibid.
[54] Ibid.
[55] Ibid.
[56] Ibid.
[57] Ibid.
[58] Ibid.
[59] Ibid.
[60] Ibid.
[61] Ibid.
[62] Ibid.
[63] Ibid.
[64] Ibid.
[65] Ibid.
[66] Ibid.
[67] Ibid.
[68] Ibid.
[69] Ibid.
[70] Ibid.

Bibliography

Air Force Cost Analysis Agency. Fuel Consumption Cost Estimating Relationship. January 2000.

Brown, Thomas, W. *Forecasting Research & Development Program Budgets Using The Weibull Model.* MS Thesis, Air Force Institue of Technology: Wright-Patterson AFB OH, 2002. (AD-A400571).

Central Intelligence Agency: The World Factbook. November 2008. https://www.cia.gov/library/publications/the-world-factbook/ (accessed November 2008).

Danigole, Mark S. "BIOFUELS: An Alternative to US Air Force Petroleum Fuel Dependency." Maxwell Air Force Base: Air University, December 2007.

Energy Information Administration. November 2008. http://tonto.eia.doe.gov/dnav/pet/pet_move_impcus_a2_nus_ep00_im0_mbbl_m.htm (accessed November 2008).

Myers, Norman. *Ultimate Security: The Environment Basis of Political Stability.* Washington, DC: ISLAND PRESS, 1996.

Neter, John, Michael H. Kutner, Christopher J. Nachtsheim, and William Wassweman. *Applied Linear Statistical Models (Fourth Edition).* Boston: MaGraw-Hill Companies, Inc., 1996.

Petersen, John L. *The Road to 2015: Profiles of the Future.* Corte Madera: Waite Group Press, 1994.

Roberts, Paul. *The End of Oil: On the Edge of a Perilous New World.* New York: Houghton Mifflin Co, 2005.

Sall, John, Ann Lehman, and Lee Creighton. "JMP Start Statistics: A Guide to Statistics and Data Analysis Using JMP® and JMP IN® Software." SAS Institute Inc., 2001.

Schwartz, Lawrence, Isabela Castaneda, Ronald L. Straight, Avery Williams. "Forecasting Fuel Consumption: USCG Aircraft and Cutters." McLean: Logistics Management Institution, January 1999.

United States Census Bureau: International Data Base (IDB). November 2008. http://www.census.gov/ipc/www/idb/ (accessed November 2008).